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Costly Arbitrage and the Lead-Lag Structure Between Value and Glamour Stocks

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COSTLY ARBITRAGE AND THE LEAD-LAG STRUCTURE

BETWEEN VALUE AND GLAMOUR STOCKS

by

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Abstract

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Motivated by the findings of Lo and Mackinlay (1990) that size premium can be partially attributed to the lead-lag relation between the returns of large stocks and those of small stocks, in this thesis we hypothesize that a possible lead-lag structure between value and glamour returns can partially explain the value premium anomaly.

The thesis consists of three chapters. Chapter I documents a pronounced lead-lag structure between value and glamour stocks: the glamour stocks lead value stocks in terms of both mean returns and residual volatilities, suggesting that value stocks delay in price adjustment to new information. To further explore the issue, we test the lead-lag price reaction to market- and firm-specific information separately in Chapters II and III. The results show that value stocks lag in absorbing both market- and firm-specific information relative to glamour stocks.

Consistent with the costly arbitrage literature, which posits that arbitrage cost is the major deterrent to market efficiency (Shleifer and Vishny 1997, Pontiff 1996, 2005, and Mendenhall 2004), our results show that value stocks are exposed to higher arbitrage cost than glamour stocks. Specifically, we find that value stocks are associated with high idiosyncratic risk that impedes the prompt price reaction to new information. That is, value stocks are exposed to higher unhedgeable fundamental risk that forces arbitrageurs to refrain form establishing positions in value stocks. This pattern does not gain support in glamour stocks. In addition, the thesis provides evidence that arbitrage risk is priced into value stock returns, suggesting that stocks subject to high arbitrage risk commands a return premium. Accordingly, value premium can be viewed, to certain extent, as compensation for bearing higher arbitrage risk, rather than systematic risk.

Dedicated to

My beloved husband, Rufeng Liu, who understands, supports, and sacrifices for my dream, and to my son, Samuel and daughter, Anya who were so lovingly patient while Mamma studied.

&

In Memory of

My mother, Gaixian Zhang 1947-2003, a wonderful woman, always willing to nurture and support my prosperity in education.

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Introduction

Lo and MacKinlay (1990) document an asymmetric information diffusion between stock returns: The returns of large-capitalization stocks almost always lead those of smaller stocks. They also demonstrate that this lead-lag relation can partially explain the observed contrarian profits. For example, if price changes of stock A lead those of stock B, a contrarian strategy may profit from buying stock B subsequent to an increase in stock A and selling stock B subsequent to a decline in stock A. Although there is a certain agreement that lead-lag structure can lead to contrarian profits (Boudoukh, Richardson, and Whitelaw 1994, Jegadeesh and Titman 1995), the lead-lag hypothesis has never been proposed to explain the value premium, the most obvious implication of the contrarian model.

The first goal of the thesis is to investigate this potential explanation for the value premium: the lead-lag relationship between returns of glamour and value stocks. Chapter I of the thesis documents pronounced asymmetric information diffusion between glamour and value stocks: the glamour stocks lead value stocks in terms of both returns and volatility, suggesting that glamour stocks react to information faster than value stocks do. Accordingly, the higher returns of glamour stock in portfolio formation period imply higher returns for value stock in the next period. In fact, if the magnitude of price increases for value stocks after portfolio formation is large enough, the book to market ratio of the value stocks will fall to the extent that they become glamour stocks in the next period. The value strategy can thus profit from buying value stocks subsequent the superior performance of glamour stocks. Therefore, the asymmetric price response to new information between value and glamour stocks, and the delayed price reaction on part of the value stocks in particular, can partially explains the observed value premium. This interpretation of the value profit is consistent with the findings of Hou and Moskowitz (2005) that firms with delayed price adjustment earn higher returns.

Then the natural question that rises is why value stocks lag behind glamour stocks in reacting to new information. Strict market efficiency requires that securities prices immediately reflect all available information and the arbitrage mechanism is the vehicle that eliminates mispricing and delivers efficiency. However, costly and risky arbitrage deters risk averse arbitrageurs from taking enough position to eliminate mispricing and restore market efficiency. Thus it takes longer for the stocks with high arbitrage cost to converge to fundamental value and fully reflect new information. Prior empirical studies investigating the effect of costly arbitrage on the existence of mispricing and delayed price adjustment to new information focus mainly on the "cost" part of the arbitrage activities (e.g. Garman and Ohlson 1981, Knez and Ready 1996, and Barber et al. 2001), not much on the "risk" part of the arbitrage activities. However, recent literature of costly arbitrage posits that arbitrage risk, or idiosyncratic risk is the largest impediment to market efficiency because arbitrageurs are unable to hedge idiosyncratic risk and thus they care more about idiosyncratic risk than systematic risk when they take trading positions. (Shleifer and Vishny 1997, and Pontiff 1996, 2005). Empirical studies also provide evidence in support of the argument that idiosyncratic risk is the largest barrier to arbitrage. For example, Ali, et al (2003) find that value effect is greater for stocks with high idiosyncratic risk, consistent with the argument that idiosyncratic risk exacerbates market inefficiency. Mendenhall (2004) provides empirical evidence that post earnings announcement drift increases with idiosyncratic risk, sugesting that idiosyncratic risk hampers the immediate price adjustment to new information.

The second goal of the thesis is to investigate whether the arbitrage cost, and in particular, idiosyncratic risk explains the slower reaction to new information on the part of value stocks. Chapter II of the thesis focuses on the asymmetric price reaction to market information between value and glamour stocks, and how the arbitrage cost might be relevant in explaining the phenomenon. Chapter III of the thesis focuses on the asymmetric price reaction to firm specific information (earnings announcements) between value and glamour stocks, and how the arbitrage cost relevant in explaining the post earnings announcement price drift.

The study contributes to the finance literature in three ways. 1) This is the first study that identifies the lead-lag relationship between returns of value stocks and those of glamour stocks, which provides a potential explanation for the value premium. 2) The thesis bridges the literature of asymmetric information assimilation and the literature of costly arbitrage by providing empirical evidence that arbitrage cost plays an important role in explaining the lead-lag relationship between value and glamour stocks. The results provide support to the argument that arbitrage cost, and idiosyncratic risk in particular, is a major impediment to market efficiency from the perspective that high arbitrage cost stocks (value stocks) lag in reacting to new information relative to the low arbitrage cost stocks (glamour stocks). 3) Last but not least, the thesis provides evidence that arbitrage risk is priced into stock returns, and stocks subject to high arbitrage risk commands a return premium. Accordingly, value premium can be viewed, to certain extent, as compensation for bearing higher arbitrage risk, rather than systematic risk.

Chapter I. The Lead-Lag Structure between Value and Glamour Stocks

I. Introduction

Motivated by the evidence of Lo and MacKinlay (1990) that the lead-lag relation between the returns of large stocks and those of small stocks partially contributes to the observed size premium, Chapter I of the thesis hypothesizes that a possible lead-lag structure between value and glamour returns can partially explain the value premium anomaly.

Chapter I is organized as follows. Section II discusses related literature and hypothesis development. Section III tests the lead-lag structure of mean returns between glamour and value portfolios. Section IV uses GARCH family specifications to test the asymmetric volatility spillover between glamour and value portfolios. Section V concludes.

II. Related Literature Review

The lead-lag structure between different size portfolios has been well documented in the finance literature. The returns of large-capitalization stocks almost always lead those of smaller stocks, suggesting an asymmetric assimilation of information across different size stocks. Ever since the seminal paper of Lo and MacKinlay (1990), who first document the empirical evidence for the transmission of information between large and small stocks, a series of studies propose and test hypotheses to explain the asymmetric information assimilation across different size stocks.

It has been well recognized that firm size per se may have little economic significance for the information transmission across firms. However, firm size may be highly correlated with some firm characteristics that are relevant to the information transmission. One explanation is that size is positively correlated with investor recognition, or the number of individuals who are interested in a firm and therefore more information is produced for large firms by those individuals (Merton 1987). Asymmetric information diffusion associated with investor recognition has gained consistent empirical support. For instance, Brennan, Jegadeesh and Swaminathan (1993) find that firms with high analyst coverage tend to respond more rapidly to market returns than do firms with low analyst coverage. Badrinath, Kale and Noe (1995) document that returns of the stocks with the higher level of institutional ownership lead returns of the stocks with the lower levels of institutional ownership. Hou and Moskowitz (2005) show that delayed firms earn higher return, and the delay premium is explained by the proxies for investor recognition such as analyst coverage and institutional ownership.

If the faster reaction to new information on the large cap stocks relative to the small cap stocks can be attributed to the positive correlation of speed of information adjustment with investor recognition, it is reasonable to conjecture that glamour stocks react faster than value stocks to new information, since glamour stocks tend to have greater investor recognition such as

greater analyst coverage and institutional ownership than value stocks. Therefore, we hypothesize that mean returns of glamour stocks will lead those of value stocks.

The asymmetric price adjustment can be reflected not only in the lead-lag relation of mean returns, but also in the unidirectional volatility spillover between portfolio returns. That is, if the return volatility of portfolio A has an impact on the return volatility of portfolio B, whereas the return volatility of portfolio B has no impact on the return volatility of portfolio A, then the conclusion can be made that the return volatility of portfolio A leads that of portfolio B. Using the GARCH family of statistical processes, Conrad, Gultekin and Kaul (1991) find that the volatility shocks to larger firms are important to the future dynamics of the returns of smaller firms as well as to their own returns. Conversely, the volatility shocks to smaller firms have no impact on either the conditional mean or the variance of the returns of larger firms. Consistent with the findings of Conrad, Gultekin and Kaul (1991) regarding the different size portfolios, we hypothesize that there exists a unidirectional volatility spillover between glamour and value portfolios, with the volatility shocks of glamour stocks having an impact on the return volatility of value stocks, but not visa versa.

According to Lo and MacKinlay (1990), lead-lag structure can partially explain the observed contrarian profits. For example, if glamour stocks lead value stocks, the higher returns of glamour stocks in the portfolio formation period imply higher returns of value stocks in the next period, thus value stocks or the loser stocks at the formation period can follow glamour stocks to be the winner of next period, generating observed value profit. Therefore the investigation of the lead-lag structure between glamour and value stocks has implications for the existence of value premium.

III. Lead-Lag Structure between Value and Glamour Mean Returns

III.1 Data

Following Davis, Fama and French (2000), portfolios are constructed in a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three

book-to-market portfolios. Controlling firm size is important because we already know from the evidence of Lo and MacKinlay (1990) that returns of larger stocks always lead the returns of smaller stocks. Holding firm size constant allows us to distinguish the value/glamour effect from a pure size effect on the lead-lag structure across stock returns. All returns are calculated in excess of the Treasury bill rate from Ibbotson Associates. The market return is the value-weighted return on all NYSE, AMEX, and NASDAQ stocks with book equity data for the previous calendar year. To be consistent with earlier studies in the asymmetric information assimilation literature (Lo and MacKinlay 1990, Conrad, Gultekin and Kaul 1991, Jegadeesh and Titman 1995), the empirical tests use weekly return data.[1] One advantage of using weekly returns rather than daily returns is that the positive cross-autocorrelation generated by different nontrading probabilities for different portfolio groups is virtually eliminated. The sample includes 2188 weekly observations for each of the six size-B/M portfolios. The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website.[2]

III.2 B/M Portfolio Statistics

Table 1 reports the size-B/M portfolio statistics. Consistent with the documentation of value premium, the mean return increases as the B/M ratio increases within both size groups. However, the standard deviation of the weekly return decreases with the B/M ratio within both size groups. In the all stock panel, the mean weekly return of value (high B/M) stocks is 0.2889, larger than the mean weekly return of the glamour (low B/M) stocks, 0.2010. However, the standard deviation of value stocks is 1.9293, smaller than the standard deviation of glamour stocks, 2.2869. These results cast doubt on the fundamental risk explanation for the value premium which claims that the higher returns of value stocks are compensation for bearing higher fundamental risk

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[1] We obtained similar results using the daily and monthly portfolio returns data.

[2] Professor Kenneth French data URL is: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library

on the part of the investors holding value stocks. In addition, there is strong tendency within both size groups for the autocorrelations to increase in terms of both absolute value and significance as the B/M ratio increases. In the all stock panel, the autocorrelation of one lag is 0.008 for glamour stocks and 0.088 for value stocks, and the Q-stat is insignificant (0.133) for glamour stocks and highly significant (16.849) for value stocks. If a slow adjustment to new information manifests itself in positive autocorrelation, this finding of stronger autocorrelation for the high B/M portfolios relative to the low B/M portfolios seems to suggest asymmetric information assimilation across B/M portfolios, with new information absorbed faster among the low B/M stocks and slower among the high B/M stocks.

[Insert Table 1 here]

III.3 Cross-Autocorrelation Tests

Following Lo and MacKinlay (1990), we investigate the lead-lag relationship in portfolio returns based on cross-autocorrelations analysis. Table 2 presents the cross-autocorrelation matrices for the weekly portfolio return series. Since the focus of our tests is to identify the relationship between value and glamour stocks, we restricted our attention to the two extreme portfolios within each size group with the lowest (R(g)) and the highest (R(v)) B/M ratios.

Consistent with our hypothesis that glamour stock returns lead value stock returns, we find that the correlations of lagged glamour portfolio returns R(g, t-1) and R(g, t-2) with the value portfolio contemporaneous returns R(v, t) are greater than the correlations of lagged value portfolio returns R(v, t-1) and R(v, t-2) with the glamour portfolio contemporaneous returns R(g, t).[3] In the all stock columns, the correlation between R(g, t-1) and R(v, t) is significant and positive, 0.0608, whereas the correlation between R(v, t-1) and R(g, t) is insignificant

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[3] We test the correlation between contemporaneous and lagged returns up to 4 weeks lag. The asymmetry between the correlations of lagged glamour portfolio returns with the value portfolio contemporaneous returns and the correlations of lagged value portfolio returns with the glamour portfolio contemporaneous returns disappears after 2 weeks lag. Therefore we only report correlation results up to 2 weeks lag.

and negative, -0.0132. The correlation between R(g, t-2) and R(v, t) is significant and positive, 0.0461, whereas the correlation between R(v, t-2) and R(g, t) is positive but insignificant, 0.0052. This pattern of asymmetry, robust in all size groups, is indicative of the lead-lag relations between the glamour portfolio returns and the value portfolio returns, with the glamour returns leading the value returns.

[Insert Table 2 here]

To further investigate the lead-lag relations in the weekly returns we estimate the following regression specifications as suggested by Badrinath, et al (1995). Again we restrict our attention to the two portfolios within each size group that has the lowest (R(g)) and the highest (R(v)) B/M ratio.

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \beta_{-2} R_{g,t-2} + \beta_{-3} R_{g,t-3} + \varepsilon_t \qquad [1]$$

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \beta_{-2} R_{v,t-2} + \beta_{-3} R_{v,t-3} + \varepsilon_t \qquad [2]$$

Where R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest and highest B/M portfolios. R(g, t-i) and R(v, t-i) are the excess return i months earlier on glamour and value portfolios, i = 1, 2, 3 in our regression. Contemporaneous and lagged returns of the lowest B/M (glamour) portfolio are predictors for returns of the highest B/M (value) portfolio in Equation[1]; Contemporaneous and lagged returns of the highest B/M (value) portfolio are predictors for returns of the lowest B/M (glamour) portfolio in Equation[2]. To be consistent with our hypothesis that glamour stock returns lead value stock returns, we expect to find that one or more of the coefficients of the lagged glamour portfolio returns in Equation[1] are positive significant, whereas the coefficients of the lagged value portfolio returns in Equation[2] are insignificant or less significant than the coefficients in Equation[1].

Table 3 reports the regression estimation results. As expected, we find a significant positive correlation between contemporaneous value weekly returns and lagged glamour weekly returns for up to a two week lag for all size groups. We also find significant negative correlation between

contemporaneous glamour weekly returns and lagged value weekly returns for up to a two week lag for all size groups. In the "all stock" column, the coefficients of one week and two week lagged glamour returns in explaining the contemporaneous value returns are both positive and significant, with 0.0458 for one week lag and 0.0284 for two week lag. One the other hand, the coefficients of one week and two week lagged value returns in explaining the contemporaneous glamour returns are both negative and significant, -0.0975 for one week lag and -0.0542 for two week lag. The existence of the significant positive correlation between the lagged glamour returns and the contemporaneous value returns provides support to the hypothesis that glamour stock returns lead the value stock returns. Furthermore, the finding of negative correlation between the lagged value returns and the contemporaneous glamour returns rejects the existence of a feed-back relationship, in which glamour returns lead (cause) value returns, and also value return lead (cause) glamour return. This thus lends further support to the unidirectional lead-lag hypothesis between glamour and value stocks.

[Insert Table 3 here]

IV. Volatility Spillover between Value and Glamour Stocks

The cross-correlation tests in Section III provide evidence supporting the existence of asymmetry in the predictability of mean returns between value and glamour stocks. Although such an asymmetry does suggest that there are important differences in the dynamics of the stock prices of firms categorized on the basis of B/M ratio, it may not necessarily imply that information is transmitted from lowest to highest B/M firms. Ross (1989) shows that the variance of price changes is related directly to the rate of flow of information. Bollerslev et al (1992) show that speculative price changes are interwoven with higher moment dependencies. Cheung and Ng (1996) also argue that volatility spillovers are important because changes in volatility reflect the arrival of information. Hence, to gain a better understanding about the asymmetric information assimilation process across value and glamour stocks, we examine empirically the pattern of stock return volatility spillover between value and glamour stocks in this section.

In the spirit of Conrad et al (1991), who find a unidirectional volatility spillover effect from larger firms to small firms, we first estimate a GARCH(1,1)-M model for the lowest B/M (glamour) and highest B/M (value) portfolios separately, and then introduce the lagged squared errors for glamour and value portfolios as an exogenous variable in the conditional variance equation of the value and glamour portfolios respectively. To be consistent with the hypothesis of the lead-lag relation between glamour and value stocks, we expect to show that the lagged squared errors for the glamour portfolios play a significant role in determining the conditional variance of the value portfolios.

IV.1 Univariate GARCH model

We apply the GARCH(1,1)-M specification to the weekly return series of the lowest B/M (glamour) and highest B/M(value) portfolios separately to derive the error terms for the volatility spillover tests. To be consistent with the models used to test the mean return spillover in section III, we also include the concurrent and lagged returns of the other portfolio in the mean return equations. Furthermore, inclusion of the lagged returns of the other portfolio in the mean return equations ensures that all asymmetry in the predictability of mean returns is purged from the error term. This is important because an asymmetric spillover in the mean return could remain in the error term and show up as asymmetric responses of conditional variances to shocks. The estimated models are:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t}$$
$$h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1} \qquad [3]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t}$$
$$h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1} \qquad [4]$$

where R(g, t) and R(v,t) are the contemporaneous excess returns of the lowest and highest B/M portfolios. R(g, t-1) and R(v, t-1) are the excess return 1 week earlier on glamour and value

portfolios. β_{-1} measures the impact of the lagged returns of the glamour (value) portfolio on the conditional mean of the value (glamour) portfolio. The σ is the standard deviation of the conditional variance of the error term.

Table 4 reports the estimation results. The coefficients of the GARCH(1,1) terms (b and c) are always statistically significant, confirming the existence of a GARCH effect and providing statistical support for the use of the GARCH specification. Consistent with the findings in Section III, we find a significant asymmetry in the predictability of mean returns between the value and glamour portfolios. The lagged weekly returns of glamour stocks are positively correlated with the contemporaneous weekly returns of value stocks while the lagged weekly returns of value stocks are negative correlated with the contemporaneous weekly returns of glamour stocks. In the "all stock" column, the coefficient of one week lagged glamour returns in explaining the contemporaneous value returns is positively significant (0.0478), while the coefficient of one week lagged value returns in explaining the contemporaneous glamour returns are negatively significant, (-0.0777). The results are robust for all three size groups, supporting the existence of a unidirectional mean return spillover from glamour stocks to value stocks.

[Insert Table 4 here]

IV.2 Unidirectional Volatility Spillover

To examine empirically whether there exists an asymmetric volatility spillover effect between value and glamour stocks, we interpret the squared residuals from Equations [3] and [4] as a "volatility shock" to value and glamour stocks respectively, and then append this "volatility shock" variable to the conditional variance of Equations [4] and [3] to estimate the relation between the conditional variance of value (glamour) portfolio returns and the lagged squared shocks to glamour (value) portfolio returns:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t}$$

$$h_{v,t} = a + b\varepsilon_{v,t-1}^{2} + ch_{v,t-1} + d\varepsilon_{g,t-1}^{2} \quad [5]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t}$$
$$h_{g,t} = a + b\varepsilon_{g,t-1}^{2} + ch_{g,t-1} + d\varepsilon_{v,t-1}^{2} \quad [6]$$

"d" measures the impact of past volatility surprises of the glamour portfolio on the conditional variance of the value portfolio in Equation[5], and in Equation [6], d measures the impact of past volatility surprises of the value portfolio on the conditional variance of the glamour portfolio. The volatility surprises, $\varepsilon_{g,t-1}^{2}$ and $\varepsilon_{v,t-1}^{2}$ are lagged squared residuals derived from Equations [4] and [3] respectively.

Table 5 reports the volatility spillover estimation results. No indications of serious model misspecification are observed. Jensen's alphas are insignificant for all size groups. The estimated coefficients of GARCH(1,1) terms (b and c) are always significant at 1%, confirming the existence of GARCH effects and providing statistical support for the use of the GARCH specification. Consistent with our expectations, we find a distinct asymmetry in volatility spillover between the glamour and value portfolios, with the past volatility surprise of the glamour portfolio positively and significantly influencing the conditional variance of the value portfolio. These coefficients are 0.0141, 0.0141 and 0.0216 for small, big and all stocks groups, respectively, whereas the past volatility surprise of the value portfolio is not significant in determining the conditional variance of the glamour portfolio. These coefficients are 1E-6, 8.8090E-20, and 6.3790E-21 for small, big and all stocks groups, respectively.

In addition, after introducing volatility spillover effects to the GARCH models, the asymmetry in the predictability of mean returns between glamour and value portfolios remains. The coefficients of lagged glamour returns in determining the contemporaneous value returns are always positive and significant. These coefficients are 0.0357, 0.0269 and 0.0473 for small, big and all stocks groups, respectively, whereas the coefficients of lagged value returns in

determining the contemporaneous glamour returns are always negative and significant. These coefficients are -0.0626, -0.0616 and -0.0777 for small, big and all stocks groups, respectively.

[Insert Table 5 here]

V. Conclusion

We empirically test the lead-lag relationship in both the mean return and conditional volatility between value and glamour portfolios in Chapter I. The results provide evidence in support of a unidirectional spillover of both mean returns and conditional volatilities between glamour and value stocks. Specifically, the glamour stocks lead the value stocks in both mean return and conditional volatility. The discovery of the lead-lag structure between value and glamour stocks provides a potential explanation for the existence of value premium. Furthermore, the lead-lag relationship implies important differences in the dynamics of the stock price changes between the value and glamour portfolios. That is, glamour stocks absorb new information faster than value stocks. To further explore this issue, we test the lead-lag price reaction to market- and firm-specific information separately in Chapters II and III.

Chapter II. Costly Arbitrage and Asymmetric Stock Price Reactions to Common Information

I. Introduction

Chapter I showed that glamour stocks lead value stocks in both mean returns and conditional volatilities, suggesting that glamour stocks react to new information faster than value stocks. However, an individual firm's stock price reflects both common information (market- and industry-level information) and firm-specific information. King (1966) provides evidence that stock returns covary with market and industry returns. Roll (1988) finds that only a small portion of stock return variation is attributable to the general market and industry movements, suggesting that the residual returns reflect the firm-specific information. Since individual firms are

influenced by both common economic fundamentals and events unique to the firms, the lead-lag relationship documented in Chapter I can be a manifestation of the asymmetric price reaction to either common information or firm specific information or both. Therefore, to further address the issue of the lead-lag structure between glamour and value stocks, we test the asymmetric stock price reaction to common information and firm-specific information separately in Chapter II and III. The role of costly arbitrage in explaining the delayed response of value stocks to new information is also investigated in these two Chapters.

Chapter II is organized as follows. Section II formally tests whether glamour stocks react to common information faster than value stocks. Section III proposes that the higher arbitrage risk borne by the value stocks relative to glamour stocks delays the flow of common information into value stocks. This section focuses on testing whether value stocks are indeed exposed to higher arbitrage costs than glamour stocks in terms of both transaction costs and holding costs. Section IV concludes.

II. Asymmetric Reactions to Market Returns

II.1 Related Literature Review

Existing research establishes an informational role for investor recognition. Brennan, Jegadeesh and Swaminathan (1993) find that firms with high analyst coverage respond more rapidly to market information than do firms with low analyst coverage. Similarly, Piotroski and Roulstone (2004) find that the covariation of stock returns with market and industry returns is positively associated with analyst forecasting activities, suggesting that analyst forecasting activities increase stocks' responsiveness to common information. Consistent with the argument that financial analyst activities accelerate the incorporation of common information into stock prices, we hypothesize that glamour stocks lead value stocks in reacting to common information, since glamour stocks tend to have greater analyst coverage than value stocks.

Brennan et al (1993) constructed a formal test to investigate the asymmetry of reaction to common information between high analyst coverage firms and low analyst coverage firms. The

test looks at the pattern of price response of zero net investment portfolios that are long in high analyst coverage stocks and short in low analyst coverage stocks to market returns, proxies for common information. The model they derived mathematically shows that when the zero net investment portfolio return is regressed on current and lagged market returns, a positive coefficient on current market return and a negative sum of the coefficients on lagged market returns will imply that high analyst coverage stocks react faster to common information than low analyst coverage stocks.

In the spirit of Brennan et al (1993), our formal tests of the difference between the speed of response to common information of portfolios G (glamour, the lowest B/M portfolio) and V (value, the highest B/M portfolio) are constructed as follows. For each size group (small, big and all) the return on a zero net investment portfolio, which is long in portfolio G and short in portfolio V, is regressed against current and lags of the market returns, proxies for common information. Essentially, we are estimating current and lagged market betas in Dimson regressions which allow for information lags exceeding one period. Recent studies provide evidence of changing risk premium and returns variability over time (Campbell, et al 2001) and support the claim that the unconditional CAPM, which specifies a constant risk premium, generates biased and inconsistent betas and alphas estimates. To deal with the problem, we employ a GARCH specification of the Dimson regressions to capture the time-varying idiosyncratic volatility, modeling Heteroscedasticity, and therefore generating efficient beta estimates. We therefore estimate the following regressions for each size group:

$$R_{g,t} - R_{v,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \qquad [1]$$

where R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest B/M (glamour) and highest B/M (value) portfolios. β_0 is the current beta and $\sum_{k=1}^{k} \beta_{-k}$ refers to the sum of lagged betas. Again following Brennan et al (1993), regressions are fitted with three and five lags (k=3 and k=5).

Consistent with the conjecture that glamour stocks react faster to common information than value stocks, we expect to find a significant positive β_0, the coefficient on current market returns and a negative $\sum_{k=1}^{k} \beta_{-k}$, the sum of coefficients on lagged market returns.

II.2 Data

The size-B/M portfolios are constructed exactly the same way as the portfolios in Chapter I (section III.1 of Chapter I).

II.3 Summary Statistics

Summary statistics are presented in Table I (section III.2 of Chapter I).

II. 4 Dimson Regression Results

Table 6 reports the Dimson regression estimation results. No indications of serious model misspecification are observed. All GARCH(1,1) terms (b, c) are always significant at 1%, confirming the existence of GARCH effects and providing statistical support for the use of the GARCH specification. The coefficients of the current market return β(0) are significantly positive for all size groups for both 3 and 5 lags. In the lag 3 regression, β(0) is 0.3025, 0.1925 and 0.2157 for small, big and all stocks respectively, indicating that glamour stocks are significantly more sensitive to contemporaneous market returns than value stocks. Furthermore, the sum of the lag coefficients ($\sum_{k=1}^{k} \beta_{-k}$) is significantly negative for all size groups for both 3 and 5 lags. In the lag 3 regression, $\sum_{k=1}^{k} \beta_{-k}$ is -0.0029, -0.0750 and -0.1212 for small, big and all stocks respectively. Not only is the sum of the lag coefficient negative, we find all the significant lagged market betas

are negative. The negative lag coefficients combined with positive current coefficients reliably imply that glamour stocks react to common information faster then value stocks.

[Insert Table 6 here]

III. Arbitrage Costs and Asymmetric Reactions to Common Information

III.1 Related Literature Review

The results in Section II show that value stocks lag behind glamour stocks in absorbing the market information into their prices. This section explores the potential factors that inhibit the value stocks from reacting to market information promptly. In other wordss, why does market efficiency, which requires prices to immediately reflect all relevant information, stumble more severely for value stocks than for glamour stocks.

Arbitrage mechanism is the vehicle that eliminates mispricing and delivers market efficiency. However, as Shleifer and Vishny (1997) suggest, almost all arbitrage is costly and risky, which makes arbitrage unprofitable, and therefore deters risk averse arbitrageurs from trading against mispricing. Specifically, stocks with higher arbitrage costs should be less attractive to arbitrageurs. On observing common market information, arbitrageurs may take smaller positions in stocks with higher arbitrage costs, and therefore mispricing persists, and takes a longer time for those stocks to trade close to their fundamental value and reflect market information. Hence the stocks associated with high arbitrage costs exhibit a delayed price adjustment to the market information.

Prior costly arbitrage literature has focused on the effect of transaction cost, the "cost" part of the arbitrage activities on market friction, however has failed to emphasize the importance of idiosyncratic risk, the "risk" part of the arbitrage activities. Transaction cost has indeed been shown to plays an important role in dissipating arbitrage profits and limiting the rational arbitrage positions (e.g. Garman and Ohlson 1981, Knez and Ready 1996, and Barber et al. 2001). However, transaction cost alone does not provide a sufficient explanation for the existence of market friction (Ali, et al 2003). Recent studies start to pay more attention to the role of

idiosyncratic risk in market inefficiency. Shleifer and Vishny (1997) argue that to specialized arbitrageurs, idiosyncratic volatility of the stock returns is of greater concern than systematic volatility, because idiosyncratic volatility can not be hedged. Similarly, Pontiff (2005) asserts that idiosyncratic risk, instead of the systematic risk, is a holding cost because systematic risk can be offset in hedge positions. Pontiff (2005) reviews the empirical studies of the role of idiosyncratic risk in mispricing, and concludes that the common theme unifying this literature is that idiosyncratic risk appears to be the most important arbitrage costs that impede market efficiency. Accordingly, we hypothesize that value stocks are exposed to both high unhedgeable idiosyncratic risk and high transaction costs that force arbitrageurs to refrain form establishing positions in value stocks, therefore, delaying incorporation of market information into stock prices.

Furthermore, since idiosyncratic volatility represents a risk to arbitrageurs, and rational arbitrageurs must trade-off the risk of their position against the expected profit of the position, they will demand a higher return for bearing higher idiosyncratic risk. Therefore we argue that idiosyncratic risk commands a risk premium. The arbitrage risk premium should be strongest among the stocks with relatively high idiosyncratic risk and low systematic risk, because for those stocks, arbitrageurs care more about idiosyncratic rather than systematic risk, and the expected return will be more responsive to the fluctuation of idiosyncratic risk than the return of the stocks with relatively low arbitrage risk. If value stocks are indeed associated with higher idiosyncratic risk, we would expect to see a stronger arbitrage risk premium for value stocks relative to glamour stocks. Our first test of the section employs a GARCH-M Dimson model to test whether returns of value stocks are more sensitive to the fluctuation of idiosyncratic risk than the returns of glamour stocks are. The test results have implications to the relative idiosyncratic risk exposure between value and glamour stocks. In addition, if idiosyncratic risk is indeed priced into returns of value stocks, but not into the returns of glamour stocks, tentative conclusions can

be made that value premium can be viewed, to certain extent, as compensation for bearing high arbitrage risk, and the value premium represents in part an arbitrage risk premium.

The second test in this section directly calculates and compares idiosyncratic risk and transaction costs between the value and glamour stocks to see if value stocks are indeed exposed to higher arbitrage costs.

III.2 GARCH-M Dimson Market Model Specification

We use a GARCH-M market model to test the relative responsiveness of returns to changes in idiosyncratic risk between value and glamour stocks to achieve three goals: First, the idiosyncratic volatility is calculated with respect to the market model so that the effect of idiosyncratic volatility on the mean return can be separated from the effect of the market risk exposure on the mean return. Second, GARCH-M specification models the relationship between conditional idiosyncratic volatility and the mean returns explicitly, showing whether the conditional idiosyncratic volatility has explanatory power beyond the market risk premium. Last, Dimson market model allows for the effect of lagged market returns on the portfolio returns, consistent with the context of the thesis, and the test conducted in last section. Therefore our regression specifications are as follows:

$$R_{v,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \gamma\sigma_t + \varepsilon_t$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \qquad [2]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \gamma\sigma_t + \varepsilon_t$$

$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \qquad [3]$$

where R(g, t) and R(v,t) are the contemporaneous excess returns of the lowest (glamour) and highest B/M (value) portfolios. β_0 is the current beta and $\sum_{k=1}^{k} \beta_{-k}$ refers to the sum of lagged betas. Regressions are fitted with five lags (k=5).[4]

Table 7 reports the GARCH-M Dimson regression estimation results. No indications of serious model misspecification are observed. All GARCH(1,1) terms (b, c) are always significant at 1%, confirming the existence of GARCH effects and providing statistical support for the use of GARCH-M specification. The main findings of table 7 are that value stocks are more responsive to changes in idiosyncratic volatility and less responsive to changes in market returns relative to glamour stocks. For all stocks regressions, the coefficient of current market return for value portfolio is 0.8704, significantly smaller than the coefficient of current market return β(0) for glamour portfolio of 1.0797. However, GARCH-M terms (γ) are significantly positive for value stocks, but not significant for glamour stocks across all size groups. The coefficients of the idiosyncratic volatilities for value stocks are 0.3889, 0.1854, and 0.1779 in small, big and all stocks regressions respectively. These findings are consistent with our hypothesis that value stocks load more on idiosyncratic risk relative to glamour stocks. Furthermore, the results that value stocks are less sensitive to market returns and more sensitive to idiosyncratic volatilities than glamour stocks imply that the value premium, the higher returns earned by value stocks than glamour stocks, should not represent compensation for bearing high systematic risk, but compensation for bearing high idiosyncratic risk or arbitrage risk on the part of value stocks instead.

[Insert Table 7 here]

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[4] Regressions fitted with 3 lags generate similar results.

III.3 Comparison of Arbitrage Costs Across B/M Portfolios

The following test directly calculates and compares the idiosyncratic risk and transaction costs between value and glamour portfolios to see whether value stocks have higher arbitrage costs exposure than glamour stocks.

1. Variables Description

To address the potential effects of arbitrage costs on the lead-lag price adjustment to market information between value and glamour stocks, this test uses residual errors from the market model to capture idiosyncratic risk, and uses price and volume to capture transaction costs. The motivation and the construction of these proxies are as follows:

A. Idiosyncratic risk

Idiosyncratic volatility poses a significant holding cost to arbitrageurs because it can not be offset in hedge positions. A stock's idiosyncratic volatility is commonly estimated as the residual variance from a regression of its return on the returns of its proper substitutes. The selection of proper substitutes varies from study to study based on the specific needs of each study. Pontiff (1996) calculates idiosyncratic risk relative to the excess return of ten mutual funds when he tests how the idiosyncratic risk relates to mispricing, measured by the close-end fund discounts. Wurgler and Zhuravskaya (2002) estimated the idiosyncratic risk relative to returns of the stocks of similar size, similar book-to-market ratio and of same industry. Other studies constructed idiosyncratic risk relative to market index returns (Ali, et al. 2003, Pontiff and Schill 2004, Mendenhall 2004). As an empirical matter, Mashruwala, et al. (2005) demonstrate that the construction of idiosyncratic volatilities does not affect the results. In this study, we estimate the idiosyncratic risk relative to the CRSP value-weighted index. To minimize the possible size and value effects on the return residuals, we also estimate the idiosyncratic volatilities using the FF-three factor model.

B. Transaction costs proxies

The transaction costs literature has shown that both price and volume are negatively associated with transaction costs: the higher the price and the volume, the lower the transaction cotss. Stoll (2000) finds that recent stock price and recent dollar trading volume are significantly related to the bid-ask spread. Similarly, Bhushan (1994) argues stock price is negatively associated with commissions, and the dollar trading volume is negatively related to the cost of trading like price pressure. In this study, we use both PRICE and VOLUME to measure transaction costs. PRICE is the closing daily stock price averaged over all trading days during a year. VOLUME is the closing daily stock price times daily shares traded averaged over all trading days during a year.

2. Sample and Data

The sample data come from two sources. Book-to-market data is from COMPUSTAT. Price, volume and return data are from the Daily CRSP. Because B/M ratio data is only available since 1986, the sample period spans from calendar year 1987 to 2005 for which complete data are available, consisting of 66,568 total firm observations, including both exchange-traded and NASDAQ stocks.

Three equal sized book-to-market portfolios are formed at the beginning of each calendar year from 1987 to 2005 based on the B/M ratio computed at prior calendar year end. Specifically, B/M ratio is defined as the ratio of book value of common equity (item #60) to market value of the equity (item #199 × item #25) at prior calendar year end. We exclude all ADR, foreign firms, and all financial companies.

Table 8 reports the descriptive statistics for all the arbitrage cost variables discussed earlier. The statistics generally agree with the pervious documentation. The distributions of PRICE and VOLUME are very comparable to those reported by Bartov, et al. (2000). In panel A, the mean of the idiosyncratic volatility of full sample is 0.0412, estimated from the market model regression of stocks' daily returns on CRSP value-weighted index and is bigger than those reported in

Wurgler and Zhuravskaya (2002) from the same market model. They report a residual variance of 0.000372 (idiosyncratic volatility is 0.0193). The difference is not surprising because their sample includes only the S&P 500, including generally large-cap firms, and exhibiting less idiosyncratic volatilities. We also find that the distributions of residual errors estimated from the market model and those estimated from the FF-three factor model are very similar. The mean residual errors differ only by 0.0004 in the full sample analysis. This is consistent with the view of Mashruwala, et al. (2005) that the estimation of idiosyncratic volatilities does not depend on the asset pricing specification.

Then we compare the statistics in panel B and C for value and glamour portfolios respectively. Consistent with our hypothesis that value stocks have higher idiosyncratic risk exposure, we find the mean idiosyncratic risk estimated from market model for value stocks (4.7%) is 0.6% higher than that of glamour stocks (4.1%). This result is robust to the alternate construction of idiosyncratic risk estimated from a FF-three factor model. Similar pattern is found for transaction cost variables. The mean price and dollar volume of value stocks are significantly lower than those of glamour stocks by $11.452 and $17.771 million respectively, indicating that value stocks are exposed to higher transaction cost than glamour stocks do.

[Insert Table 8 here]

3. Detailed Comparison Results

Table 9 reports the detailed comparison of arbitrage costs across three equally sized B/M ratio portfolios for each year over the 1987 to 2005 period. Consistent with the summary statistics results in Table 8, we find that idiosyncratic volatilities of value stocks are significantly higher than those of glamour stocks in 13 out of 19 years. Price and the volume of value stocks are significantly lower than those of glamour stocks in all years. The results provides evidence that value stocks are exposed to both higher idiosyncratic risk and higher transaction costs, causing a slower response to market information on the part of the value stocks relative to glamour stocks.

[Insert Table 9 here]

IV. Conclusion

Chapter II formally tests asymmetric price response to common information between value and glamour stocks. Consistent with the findings of Chapter I that value stocks lag behind glamour stocks in terms of both mean return and volatilities, the results in Chapter II show that the value stocks 'response to market information is slower than that of glamour stocks. We propose that the higher arbitrage costs borne by the value stocks relative to the glamour stocks is the reason for slow absorption of common information into value stock prices. Through a thorough comparison of arbitrage costs of value and glamour stocks, we find strong evidence that value stocks are associated with both higher idiosyncratic risk and higher transaction costs than are glamour stocks. This is consistent with our hypothesis that the slower price adjustment to market information on the part of value stocks can be partially attributed to the higher arbitrage costs borne by the value stocks. Furthermore, the results from testing the relationship between idiosyncratic risk and expected returns show that idiosyncratic risk is priced into the returns of value stocks, but not into the returns of glamour stocks, suggesting that value stocks load more on idiosyncratic risk. The results also have implications on explaining the existence of value premium, that is, value premium may represent an arbitrage premium, and value profit is compensation for bearing higher arbitrage risk.

Chapter III. Costly Arbitrage and Asymmetric Price Drift to Firm-Specific Information – Earnings Announcement

I. Introduction

Chapter II showed that values stocks are associated with high arbitrage costs that forces arbitrageurs to refrain from establishing positions in value stocks, leading to a slower price adjustment to market information. Then the next natural question is whether the higher arbitrage costs borne by value stocks causes slower price reaction to firm-specific information as well.

Mendenhall (2004) shows that the post earnings announcement drift over the next quarter is stronger for firms with higher idiosyncratic risk, suggesting that high idiosyncratic risk impedes fast flow of firm-specific information into stock prices. Consistent with his finding, we hypothesize in Chapter III that value stocks react to firm-specific information more slowly than glamour stocks, because they are associated with high idiosyncratic risk.

Chapter III is organized as follows. Section II discusses the related literature and develops hypotheses. Section III formally tests whether glamour stocks react to firm-specific information more promptly than do value stocks. Since slower price adjustment to the firm-specific information is associated with longer and stronger price drift after the event dates, we expect to find that value stocks experience longer and stronger post event price drift than do glamour stocks. Section IV proposes that the higher arbitrage costs borne by the value stocks relative to glamour stocks is the reason for slower response to firm-specific information on the part of value stocks, resulting in longer and stronger post event price drift, and tests how idiosyncratic risk explains the asymmetric post earnings announcement drift between value and glamour stocks.

II. Related Literature Review

Our main hypothesis in Chapter III is that high idiosyncratic risk borne by value stocks causes a slower price adjustment to firm-specific information. This hypothesis is motivated by two findings. First, idiosyncratic risk is a major deterrent to market efficiency. Second, value stocks are exposed to higher idiosyncratic risk.

Existing research has established the role of idiosyncratic risk in impeding market efficiency. Shleifer and Vishny (1997) argue that idiosyncratic risk matters more to specialized arbitrageurs than systematic risk does, because idiosyncratic risk can not be hedged. Pontiff (2005) reviews the empirical studies on the role of idiosyncratic risk in mispricing, and concludes that idiosyncratic risk appears to be the most important deterrent to market efficiency. On observing firm-specific information, arbitrageurs may take smaller positions in stocks with higher arbitrage costs. If investors tend to underreact to the value implications of firm news, then high arbitrage

cost stocks which are less attractive to arbitrageurs will produce more severe underreation and exhibit greater drift. Mendenhall (2004) shows that post earnings announcement drift over the next quarter is stronger for firms with higher idiosyncratic risk, suggesting that securities subject to higher idiosyncratic risk react to firm-specific information more slowly than securities subject to lower idiosyncratic risk. Motivated by the above evidence from the literature and the our findings in Chapter II that value stocks are exposed to higher idiosyncratic risk than are glamour stocks, we hypothesize that the high idiosyncratic risk borne by value stocks impedes the prompt flow of firm-specific information into stock prices, resulting in greater post event price drift.

Since a slow response to firm-specific information can be manifested through stronger and longer price drift after the event date, we test the asymmetric price reaction to firm-specific information between value and glamour stocks by comparing their post event price drift. Specifically, we test and compare the post earnings announcement drift (PEAD) between value and glamour stocks.

Post Earnings Announcement Drift (PEAD) is the tendency for stocks to earn high positive average abnormal returns in the months subsequent to positive earnings surprises, and to earn negative average abnormal returns in the months subsequent to negative earnings surprises. PEAD has been documented in the literature for at least 3 decades. This enduring feature of stock prices to gradually, rather than immediately adjust to earnings surprises has been widely regarded as an anomaly from the perspective of efficient market hypothesis (e.g., Ball and Brown 1968, Bernard and Thomas 1989, 1990, and Bernard, Thomas and Wahlen 1997).

Bernard and Thomas (1990) provide evidence in support of the market inefficiency explanation. They show that following the earnings surprise, the three-day stock returns around subsequent earnings announcements exhibit positive and declining first, second, and third order autocorrelation and negative fourth order autocorrelation. This autocorrelation pattern is consistent with the market inefficiency hypothesis that stock prices initially underreact to earnings surprise, and then drift in the same direction in subsequent months.

If PEAD indeed represents a delayed price response to new information, as argued by Bernard and Thomas (1989, 1990, and 1992), the earnings announcement serves as an appropriate context in which we can test the asymmetric price response to firm-specific information between value and glamour stocks. To be consistent with our main hypothesis that value stocks absorb firm-specific information more slowly than glamour stocks, we expect to see that value stocks experience stronger and longer post earnings announcement drift than do glamour stocks. In other wordss, if both value and glamour stocks underreact to earnings surprises, value stocks should underreact more severely, resulting in stronger and longer post announcement drift. Our testable hypothesis is that value stocks should produce relatively higher abnormal returns following good news and relatively lower abnormal returns following bad news.

III. Asymmetric Post Earnings Announcement Drift between Value and Glamour Stocks

III.1 Sample and Methodology

The sample data come from two sources. Book-to-market data and quarterly earning announcement date (item RDQ in COMPUSTAT) come from COMPUSTAT. Returns come from the CRSP. The sample period spans from the first fiscal quarter of 1994 through the third fiscal quarter of 2005. [5]

We use quarterly earnings announcements as firm-specific news events. Following Franzzini (2006), earnings surprises are measured using the market model cumulative abnormal returns in a 3-day window (-1, 0 and 1) around the quarterly earnings announcement dates. Following Doukas et al (2002), book-to-market is defined as the ratio of book value of common equity (item #60) to market value of the equity (item #199 × item #25) at the end of the fiscal year preceding the quarterly earnings announcement. We exclude all ADR, foreign firms, and all financial companies. To avoid any potential IPO effects, we exclude stocks with less than 255 days of

[5] The quarterly earning announcement date (COMPUSTAT item RDQ) is only available for fiscal period of first quarter of 1994 to the third quarter of 2005.

return data prior to the earnings announcement dates on CRSP. The final sample includes 154,864 total firm observations.

To test the hypothesis that value stocks are associated with relatively higher (lower) abnormal returns following good (bad) news, we assign stocks to portfolios based on the nature of the news and the B/M ratio. This is a standard approach in asset pricing, which reduces return variability. Starting from the first quarter of 1994, at each quarterly earnings announcement we classify earnings surprises into three equal sized news groups based on the market model cumulative abnormal return in the 3-day window (-1, 0, 1), and we define the group with the lowest 33% CAR as the bad news group and the group with the highest 33% CAR as the good news group. Within both good and bad news groups, stocks are further sorted into five equally sized B/M quintiles based on the B/M ratio calculated at the end of the fiscal year preceding the quarterly earnings announcement.

III.2 Empirical Tests

A. Portfolio Post-Earnings Announcement Returns by B/M Ratio

The first set of the empirical tests examines the variation in post-earnings announcement returns across B/M quintile portfolios. Table 10 reports the average monthly portfolio returns at month (t+1), (t+2), and (t+3) following the earnings announcement. The three news groups are sorted based on the earnings surprise at month t, and the five B/M portfolios are sorted based on the B/M ratio calculated at the end of the fiscal year preceding the earnings announcement. Our attention falls on the lowest 20% (glamour) and the highest 20% (value) portfolios, and we expect to see that value stocks generate higher (lower) monthly returns following good (bad) news relative to the glamour stocks in each of the three post-earnings announcement months. Since earnings news is released on a quarterly basis, the focus of the analysis is on the short-term underreaction, and our tests are only designed for three months following the earnings news. Consistent with our expectations, we find that value stocks produce significant higher monthly returns than glamour stocks in each of three months following the good earnings surprise. The

results show that value stocks outperform glamour stocks by 1.50%, 1.53% and 1.78% in the first, second, and the third post-earnings announcement months respectively. For the bad news cases, however, value stocks do not seem to produce lower post-earnings monthly returns than glamour stocks. In fact, glamour stocks have lower monthly returns than value stocks in all three months subsequent to earnings announcements. Does this result contradict our hypothesis? If we take into consideration the value premium evidence that value stocks always earn higher returns than glamour stocks, we can conclude that the lower post earnings announcement monthly return following bad news on the part of glamour stocks is not surprising and it does not necessarily imply that glamour stocks exhibit stronger underreaction to bad news than value stocks. However, since we do not control for the size and value effect in the analysis of monthly raw returns, comparison of the post earnings announcement raw returns can not provide us with conclusive evidence as to which portfolio, value or glamour, is associated with a stronger price drift.

[Insert Table 10 here]

B. Post-Earnings Announcement Drift, Monthly Alphas by B/M Ratio

To purge the drift factor from the size and value premium effect, we compute abnormal returns from a regression of the portfolio excess returns on contemporaneous Fama and French factors downloaded from Professor French's website. If the three factor model can capture the cross-sectional variation in stock returns, the intercept from the following regression should be statistically indistinguishable from zero.

$$R_{it} = \alpha + \beta R_{mt} + \delta SMB_t + \phi HML_t + \varepsilon_{it} \qquad [1]$$

i = value, glamour portfolio

Where R_{it} is the monthly return of the highest (value) and the lowest B/M (glamour) portfolios in excess of one-month treasury bill rate. R_{mt} is the value-weighted market return in excess of one-month treasury bill rate. SMB and HML are size premium and value premium factors. The Alphas represent the abnormal returns. Positive α following good news indicates the presence of

post event drift, and the opposite is true for bad news. Under the hypothesis that value stocks produce stronger and longer drift than glamour stocks, we expect to see larger and longer lasting post earnings announcement alphas for value stocks.

Table 11 reports the monthly alphas of value and glamour portfolios for each of the three months subsequent to earnings announcements. In the cases of good news, significantly positive alphas are observed for value stocks in each of the three months following earnings announcements. The risk-adjusted returns for value stocks are 0.8527%, 1.7069%, and 2.8412% in the first, second and third month following the good news, respectively. On the other hand, glamour stocks produce significant positive returns only in the second month following the good news, and both the magnitude (0.5025%) and the significance (t=2.40) of the risk-adjusted return is much smaller than those of value stocks (1.7069%, t=8.87). For the bad earnings announcements, value stocks produce significantly negative alphas (-0.7945%, t=-3.91) in the first month following the bad news. On the other hand, neither significant negative nor positive price drift is observed for glamour stocks, suggesting that glamour stocks do not under- or over-react to bad earnings announcements. To summarize, the monthly alpha results show that value stocks exhibit stronger and longer post earnings announcement drift than glamour stocks following both good and bad earnings announcements, therefore, confirming our hypothesis that value stocks react more slowly to firm-specific information.

In addition to the findings that value stocks exhibit a strong underreaction to earnings announcements, there is evidence that value stocks overreact to bad earnings announcements after an initial underreaction. The risk-adjusted monthly returns for value stocks are significantly positive in the second (1.4567%, t=6.93) and third months (1.6064%, t=6.63) following bad earnings announcements. The findings that value stocks exhibit underreation in the first month and overreaction in the second and third months subsequent to bad earnings announcements are consistent with the unified theory of short-term underreaction and long-term overreaction to new information (Hong and Stein, 1999), which predicts that price reversal should be more

pronounced in the stocks for which information diffuses more slowly. The results also provide explanations for the puzzles we observe in test A, that is, why value stocks have higher monthly returns than glamour stocks in the second and third month following bad earnings announcements. It is an overreaction in value stocks instead of a stronger underreaction in glamour stocks following bad earnings surprises that contributes to the phenomena. In general both the underreaction and overreaction market biases are heavily loaded in value stocks instead of glamour stocks following earnings announcement surprises, suggesting that the high arbitrage costs borne by value stocks force arbitrageurs to refrain from taking positions in eliminating temporary mispricing in value stocks. On the other hand, glamour stocks are associated with low arbitrage costs, hence arbitrageurs are more willing to take positions in eliminating temporary mispricing in glamour stocks, and therefore, no pronounced underreaction or overreaction is observed for glamour stocks following earnings announcements.

Another finding worth noting is that good earnings announcements produce more severe price drift than do bad earnings announcements. A significant negative PEAD occurs only in the first month following bad earnings announcements in value stocks, whereas the significant positive price drift following good earnings announcements is observed in both value and glamour stocks, and lasts for three months for value stocks. These results imply that stocks react to negative earnings surprises more promptly and strongly than they do to positive earnings surprises. In fact, we find that value stocks overreact to bad earnings surprises. This is consistent with the documented asymmetric price response to good versus bad news. That is, bad news triggers a bigger shock to security prices than does good news, and the market reacts more strongly to bad news than to good news (Bernard, Thomas, and Wahlen 1997, La Porta, Lakonishock, Shleifer and Vishny 1997, Skinner and Sloan 1998, and Conrad, Cornell and Landsman 1999).

[Insert Table 11 here]

IV. Arbitrage Costs and Asymmetric Post Earnings Announcement Drift

Consistent with our main hypothesis of this chapter that value stocks react more slowly than glamour stocks to firm-specific information due to high arbitrage costs, Section III showed that value stocks are indeed associated with stronger and longer post earnings announcements drift than glamour stocks by comparing the monthly alphas in the months following the earnings announcements. In Section IV, we follow the procedure of Mendenhall (2004) to empirically test the role of idiosyncratic risk in explaining the delayed response to firm-specific information in value stocks.

IV.1Variables Description

Mendenhall (2004) finds a significant positive relationship between idiosyncratic risk and PEAD by regressing PEAD against idiosyncratic risk and transaction cost variables. We employ similar regressions to test the relationship between idiosyncratic risk and PEAD, except we add B/M ratio as an additional variable in explaining the drift. Consistent with the findings in Section III that value stocks have a stronger and longer PEAD, we expect to see that the B/M ratio is positively associated with the PEAD when the B/M ratio is the explanatory variable alone. However, we expect that the B/M ratio will lose its significance after we control for the arbitrage costs in the regression, if the higher arbitrage cost is the underlying reason for the stronger and longer price drift in the value stocks. The motivation and the construction of the variables are as follows:

1. Dependent Variable: Post-earnings announcement abnormal returns

We measure post-earnings announcement abnormal returns as the compound abnormal return from the first month through the third month following the earnings announcement. The compound return is computed as the buy and hold return on each stock in the sample minus the buy-and-hold return on the CRSP value weighted index:

$$QEA_{i,q} = \prod_{t=1}^{3}(1 + RET_{i,q,t}) - \prod_{t=1}^{3}(1 + RET_{mkt,q,t}) \qquad [2]$$

where $QEA_{i,q}$ is stock i 's compound return from the first month through the third month following quarter q 's earnings announcement. $RET_{i,q,t}$ is the raw return of the stock i for month t relative to the earnings announcement month for quarter q. $RET_{mkt,q,t}$ is the CRSP value weighted index return for month t relative to the earnings announcement month for quarter q. Months, designated by t, run from 1 month to 3 months relative to the earnings announcement month.

2. Explanatory Variables

A. Earnings surprise

As described in Section II, the earnings surprise metric is the 3-day cumulative abnormal return (-1, 0, 1) around the earnings announcement. Using the cumulative abnormal returns around the earnings announcement day provides a clean and easy way to measure earnings surprises since they do not require a model for expected earnings. We simply refer to this variable as CAR(-1, +1).

B. B/M ratio

As described in Section II, the book-to-market is calculated as the ratio of the book value of common equity (item #60) to the market value of the equity (item #199 × item #25) at the end of the fiscal year preceding the quarterly earnings announcement.

C. Idiosyncratic risk

As described in Chapter II, we estimate the idiosyncratic risk relative to the CRSP value-weighted index, and the mean residual error from market model regression is estimated over days -255 to -2 relative to the announcement.

D. Transaction cost: Volume

We use dollar volume to measure the transaction cost. To minimize over-specification concerns, we do not include price in the regression estimation, since we find a high positive correlations between price and B/M ratio, and a high negative correlation between price and

idiosyncratic risk. In addition, Mendenhall (2004) finds no relationship between price and post earnings announcement drift. As in Mendenhall (2004), VOLUME is the closing daily stock price times daily shares traded averaged over trading days -255 to -2 relative to the announcement.

3. Transformations of the variables

To account for possible nonlinearities between the dependent and explanatory variables, Bernard and Thomas (1990), Bhushan (1994), Bartov et al. (2000) and Mendenhall (2004), use rank scores for their earnings surprise variable and the explanatory variables. For the same reasons, we transform each explanatory variable (CAR, BM, IDIO, and VOLUME) into coded scores based on their rank within pooled earnings announcement observations, and then scale the coded scores from 0.0 to 1.0. Employing the procedure of Mendenhall (2004), we then subtract 0.5 from the coded scores. Therefore our final coded scores for each variable range between -0.5 to +0.5. Coding independent variables from -0.5 to +0.5 allows the intercept of a regression of abnormal returns on a dependent variable to represent the abnormal returns for a hypothetical median observation between the two middle deciles of the independent variable, which should be close to zero. The slope coefficient can then be interpreted as the difference in abnormal returns between the highest and the lowest deciles of the independent variable.

IV.2 Determinants of Asymmetric Post-Earnings Announcement Drift between Value and Glamour Stocks

To address the issue of how idiosyncratic risk contributing to the asymmetric post earnings announcement drift between value and glamour stocks, we modify Mendenhall's (2004) regression by adding B/M ratio as an extra explanatory variable, and expect to see that the idiosyncratic risk dominates the B/M ratio in explaining the post earnings announcement drift:

$$QEA_{i,q} = a + bCAR_{i,q} + c(CAR_{i,q} * BM_{i,q}) + d(CAR_{i,q} * IDIO_{i,q}) + e(CAR_{i,q} * VOLUME_{i,q}) + \varepsilon_{i,q} \quad [3]$$

where $QEA_{i,q}$ is stock i 's compound abnormal return from the first month through the third month following quarter q 's earnings announcement. The compound abnormal return is

computed as the buy and hold compound return on each stock minus the buy-and-hold return on the CRSP value weighted index. $CAR_{i,q}$ is the market model cumulative abnormal return for the 3-day window (-1, 0, 1) around the earnings announcement for stock i in quarter q. BM is the B/M ratio calculated at the end of the fiscal year preceding the announcement. $IDIO_{i,q}$ is the mean residual error from the market model regression estimated over days -255 to -2 relative to the announcement for stock i in quarter q. $VOLUME_{i,q}$ is the closing daily stock price times daily shares traded averaged over trading days -255 to -2 relative to the announcement for stock i in quarter q.

As in Mendenhall (2004), we investigate the relationship between arbitrage costs and the PEAD through assessing whether arbitrage cost variables have an impact on the earnings surprise and PEAD relationship. In other words, we use interaction variables, the interaction between CAR and the arbitrage cost variables, to test how the relationship between the earnings surprise and price drift varies with various arbitrage costs of the firm observations. As we discussed above, coding earnings surprise variable CAR from -0.5 to +0.5 allows interpretation of the coefficient on CAR as the average difference in abnormal returns between the observations in the highest and lowest CAR deciles. Coding other explanatory variables from -0.5 to +0.5 allows the interpretation of the coefficient on each interaction variable to be the additional spread in abnormal returns between high and low CAR stocks, for observations in the highest versus the lowest deciles of the arbitrage cost variables.

Table 12 reports the estimation results of the regression [3]. Panel A reports the estimation results using as the dependent variable, QEA, the abnormal return compounded 3 months following the earnings announcement. Compounding 3 months is the standard practice for calculating quarterly abnormal returns. However, it raises the concern that the 3 month compound return may be affected by subsequent earnings announcements which usually occur in the third month following the earnings announcement. To eliminate the possibility that the third month

abnormal return is generated by the subsequent earnings announcement, we also report the estimation results when the dependent variable QEA is the abnormal return compounded only 2 months following the earnings announcement in Panel B.

Panels A and B produce very similar results. We find significant positive coefficients on CAR in all regressions, suggesting that, for observations with median arbitrage costs, the highest CAR decile produces higher post earnings announcement abnormal returns than the lowest CAR decile. In Panel A, the coefficient of CAR of 1.662 indicates that for observations with median arbitrage costs, the highest CAR decile produces 3-month abnormal returns 1.662% higher than the lowest CAR decile.

The main result in Table 12 is that without controlling for arbitrage cost variables (idiosyncratic risk and volume), the B/M ratio plays a significant role in determining post earnings announcement drift. The coefficients of the interaction variable CAR*BM are 0.543 (t=2.37) and 0.483 (t=1.74) for 3-month and 2-month abnormal returns, respectively, indicating that the spread between the abnormal returns of the highest and lowest earnings surprise deciles is 0.543% and 0.483% larger for firms in the highest B/M ratio decile than for firms in lowest B/M ratio decile in the second and third month following the earnings announcement respectively. However, when we control for the idiosyncratic risk and dollar volume of the stock, the B/M ratio no longer plays any role in determining the post earnings announcement drift. Instead, we observe significant coefficients for both arbitrage cost variables. Specifically, idiosyncratic risk is positively correlated with the price drift, and volume is negative correlated with the price drift, suggesting that high arbitrage costs are associated with a stronger and longer drift. The results that arbitrage cost variables dominate the B/M ratio in explaining the price drift lends support to our main hypothesis that higher arbitrage costs borne by value stocks, and not the B/M ratio per se, contribute to the slower price adjustment to firm-specific information for value stocks.

In addition, the results show that idiosyncratic risk plays a major role in determining the price drift. The coefficients of idiosyncratic risk are larger than those of volume in both magnitude and

significance. The coefficients of the interaction between IDIO and CAR are 1.348 (t=4.86) and 1.034 (t=3.08) for 3-month and 2-month abnormal returns, respectively, indicating that the spread between the abnormal returns of the highest and lowest earnings surprise deciles is 1.348% and 1.034% larger for firms in the highest idiosyncratic risk decile than for firms in lowest idiosyncratic risk decile in the second and third month following the earnings announcement respectively. Whereas the coefficients of the interaction between VOLUME and CAR are -0.573 (t=-2.01) and -0.553 (t=-1.60) for 3-month and 2-month abnormal return respectively, only about one half of the magnitude of the coefficients of the idiosyncratic risk interaction variable. In fact, the volume interaction variable is only significant in determining the 3-month price drift, and its t-statistic (t=-2.01) is much smaller than the t-statistic of the idiosyncratic risk interaction variable for the 3-month abnormal return (t=4.86). These results are consistent with Pontiff's argument that idiosyncratic risk is the single most important impediment to market efficiency.

[Insert Table 12 here]

IV.3 Determinants of Asymmetric Post-Earnings Announcement Drift between Value and Glamour stocks: Extreme Earnings News Analysis

In order to test the relationship between idiosyncratic risk and price drift directly without using interactive terms with earnings surprise, Mendenhall (2004) focuses his second regression tests on a subsample of observations with extreme good or bad earnings surprises. He argues that in the extreme news deciles, the earnings surprise and drift relationship is essentially flat, therefore there is no need to control for earnings surprise for the extreme news subsample.

We define earnings surprises in the highest (lowest) 10% CAR decile as extreme good (bad) news. Within these extreme earnings surprise deciles, we find low correlations of 0.01 and 0.03 between CAR and the 3-month post earnings announcement abnormal returns for good and bad news deciles respectively, indicating that the effect of CAR on the price drift is negligible for the extreme news observations. Therefore, following Mendenhall (2004), we pool observations in the

extreme good and bad news deciles together and estimate the following regression for the extreme news subsample:

$$QEA_{i,q} = a + b(BM_{i,q}) + c(IDIO_{i,q}) + d(VOLUME_{i,q}) + \varepsilon_{i,q} \qquad [4]$$

We specify QEA as the dependent variable for extreme good news announcements and QEA times -1.0 as the dependent variable for extreme bad news announcements. All explanatory variables for this regression are coded decile score ranging from -0.5 to 0.5 based on their ranking within the extreme earnings announcements observations. Unlike regressions [3], there is no interactive specification in the regression [4], each coefficient can be simply interpreted as the effect of the explanatory variable on the post earnings announcement abnormal returns.

Panels A and B on Table 13 report the estimation results for the extreme news observations when the dependent variable QEA is the abnormal return compounded 3 months and 2 months following the earnings announcement respectively. Consistent with earlier results, idiosyncratic risk dominates the B/M ratio in determining the post earnings announcements drift. The coefficients of idiosyncratic risk are 0.688 (t=2.96) and 0.521 (t=1.83) for 3-month abnormal returns and 2-months abnormal returns respectively, indicating that for the extreme news observations, the highest idiosyncratic risk decile exhibits positive (negative) 3-month abnormal returns for good-news (bad-news) observations 0.688% higher (lower) than those in the lowest idiosyncratic risk decile, and the spread in the 2-month abnormal returns between the highest and lowest idiosyncratic risk deciles is 0.521 percentage points. In addition, the coefficients on VOLUME are negative, suggesting a positive correlation between the transaction cost and price drift. However, they are not significant. These results provide additional evidence that the idiosyncratic risk is the single, most important determinant of the post earnings announcement drift.

[Insert Table 13 here]

IV.4 Asymmetric Drift - Idiosyncratic Risk Relationship between Value and Glamour stocks

The above regression test for the entire sample provides evidence that the post earnings announcement drift increases in idiosyncratic risk. We then run the following regression for value and glamour stocks separately to test explicitly how idiosyncratic risk contributes to the asymmetric price adjustment to the earnings announcement between value and glamour stocks. Specifically, we are interested in investigating how the relationship between idiosyncratic risk and price drift differs between value stocks and glamour stocks.

$$QEA_{i,q} = a + bCAR_{i,q} + c(CAR_{i,q} * IDIO_{i,q}) + d(CAR_{i,q} * VOLUME_{i,q}) + \varepsilon_{i,q} \qquad [5]$$

The construction of the variables has been discussed under Equation [3]. The B/M portfolios are sorted based on the B/M ratio calculated at the end of the fiscal year preceding the earnings announcement for the pooled earnings announcement observations. We define the lowest 20% B/M quintile as the glamour portfolio and the highest 20% B/M quintile as the value portfolio. All three independent variables have been converted to coded scores ranging from -0.5 to 0.5 based on their ranking within the value and glamour portfolios separately.

To be consistent with our hypothesis that value stocks are exposed to high arbitrage costs that impede arbitrageurs from establishing positions in eliminating mispricing, resulting in stronger and longer price drift following earnings announcements, we expect to see a higher loading of arbitrage cost in value stocks than in glamour stocks.

Table 14 presents the regression results for value and glamour stocks separately. The significant positive relationship between earnings announcement drift and idiosyncratic risk is observed in value stocks only. The coefficients of the interaction variable CAR*IDIO are 1.310 (t=2.04) and 0.646 (t=0.95) for value and glamour stocks respectively, indicating that the spread between the abnormal returns of the highest and lowest earnings surprise deciles is 1.310% larger for firms in the highest idiosyncratic risk decile than for firms in lowest idiosyncratic risk decile for value stocks. However a similar pattern is not seen for glamour stocks. The asymmetric

sensitivities of price drift to idiosyncratic risk between value and glamour stocks suggests that idiosyncratic risk is more heavily loaded in value stocks than in glamour stocks, therefore the positive association between idiosyncratic risk and price drift is more pronounced for value stocks than for glamour stocks. These results provide evidence in support of our main hypothesis that the asymmetric idiosyncratic risk loading contributes to the asymmetric price adjustment to firm-specific information between value and glamour stocks. Specifically, the high idiosyncratic risk in value stocks is attributable to their slower reaction to earnings announcements.

[Insert Table 14 here]

III. Conclusion

Chapter III explores the asymmetric price adjustment to firm-specific information between value and glamour stocks. Consistent with the documentation in Chapter I that glamour stocks react to new information faster than value stocks, we find that value stocks generate stronger and longer post-earnings announcement drift than do glamour stocks. We propose and test the hypothesis that the higher arbitrage risk borne by the value stocks relative to glamour stocks delays the diffusion of firm information into value stock prices. We find confirming evidence that price drift increases in arbitrage costs. Specifically, idiosyncratic volatility exhibits a consistent positive effect on the abnormal returns. However, the transaction cost variables produce some mixed results. This finding lends support to the argument that idiosyncratic risk is the single largest deterrent to market efficiency, and thus a major determinant of the asymmetric price drift between value and glamour stocks.

Conclusion

Motivated by the findings of Lo and MacKinlay (1990) that size premium can be partially attributed to the lead-lag relation between the returns of large stocks and those of small stocks, in

this thesis we hypothesize that a possible lead-lag structure between value and glamour returns can partially explain the value premium anomaly.

The first chapter finds that glamour stocks lead value stocks in terms of both mean returns and volatility spillover, indicating that glamour stocks react to new information faster than do value stocks. To investigate the issue further, we test the asymmetric price reaction to market- and firm-specific information between value and glamour stocks separately. We find confirming evidence that value stocks lag in absorbing both market- and firm-specific information relative to glamour stocks.

But why is information diffusion slower in value stocks than in glamour stocks? Motivated by the costly arbitrage literature, which posits that arbitrage cost is the major deterrent to market efficiency (Shleifer and Vishny 1997, Pontiff 1996, 2005, and Mendenhall 2004), we propose and empirically test the hypothesis that the high arbitrage cost borne by the value stocks is the culprit that delays the information flow into the value stocks. Consistent with the costly arbitrage literature, our results show that value stocks are exposed to higher arbitrage costs than are glamour stocks. Specifically, we find that value stocks are associated with a high idiosyncratic risk that impedes a prompt price reaction to new information. That is, value stocks are exposed to a higher unhedgeable risk that forces arbitrageurs to refrain from establishing positions in value stocks. This pattern is not reflected in glamour stocks.

Not only do we find that arbitrage risk impedes information diffusion, causing delayed price adjustment on part of the value stocks, we provide evidence that the idiosyncratic risk is a priced risk factor that demands risk premium, and value premium can be explained as compensation for bearing high arbitrage risk.

To sum up, this thesis documents a lead-lag relationship between returns of value stocks and those of glamour stocks, and provides empirical evidence that arbitrage cost, and in particular, idiosyncratic risk, can partially explain the lead-lag price adjustment to new information between value and glamour stocks.

References

Ali, A., L. S. Hwang, and M. A. Trombley. 2003. "Arbitrage Risk and the Book-to-Market Anomaly." *Journal of Financial Economics*, vol. 69, 355-373.

Ball, R. and P. Brown. 1968. "An Empirical Evaluation of Accounting Income Numbers." *Journal of Accounting Research* (Autumn 1968): 159-178.

Badrinath, S.G., J.R., Kale, and T.H. Noe. 1995. "Of Shepherds, Sheep, and the Cross-autocorrelation in Equity Returns." *The Review of Financial Studies*, vol. 8, No. 2, 401-430.

Barber, B., R. Lehavy, M. McNichols, and B. Trueman. 2001. "Can Investors Profit from the prophets? Security Analyst Recommendations and Stock Returns." *Journal of Finance*, Vol. 56, 531-563.

Bartov, E., S. Radhakrishnan, and I. Krinsky. 2000. "Investor Sophistication and Patterns in Stock Returns after Earnings Announcements." *Accounting Review*, vol. 75, 43-63.

Bernard, V. and J. Thomas. 1989. " Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?" *Journal of Accounting Research*, vol. 27, 1-36.

Bernard, V and J. Thomas. 1990. "Evidence That stock Prices Do Not Fully Reflect the Implications of Current Earnings for Future Earnings." *Journal of Accounting and Economics*, vol. 13, 305-340.

Bernard, V., J. Thomas, and J. Wahlen. 1997. "Accounting-Based Stock Price Anomalies: Separating Market Inefficiencies from Risk." *Contemporary Accounting Research,* vol.14, 89-136.

Bollerslev, T. and J. M., Wooldridge. 1992. "Quasi-Maximum Likelihood Estimation of Dynamic Models with Time-Varying Covariances." *Econometric Reviews*, vol. 11, 143-172.

Boudoukh, J., M. P. Richardson, and R. F. Whitelaw. 1994. "A Tale of Three Schools: Insights on Autocorrelations of Short-Horizon Stock Returns." *Review of Financial Studies,* vol. 7, 539-573.

Brennan, J. M., N. Jegadeesh, and B. Swaminathan. 1993. "Investment Analysis and the Adjustment of Stock Prices to Common Information." *The Review of Financial Studies*, vol. 6, No. 4, 799-824.

Bhushan, R. 1994. "An Informational Efficiency Perspective on the Post-Earnings Announcement Drift." *Journal of Accounting and Economics*, Vol. 18, 45-65.

Campbell, J, Y., M. Lettau, B. G. Malkiel, and Y. Xu. 2001. "Have Individual Stocks Become More Volatile?" *Journal of Finance*, Vol. 56, 1-43.

Cheung, Y.W. and L. K. Ng. 1996. " A Causality-in-Variance Test and its Implications to Financial Market Prices." *Journal of Econometrics*. Vol. 72, 33-48.

Conrad, J., M.N. Gultekin, and G. Kaul. 1991. "Asymmetric Predictability of Conditional Variances." *The Review of Financial Studies*, vol. 4, No. 4, 597-622.

Conrad, J., B. Cornell and W. Landsman. 2002. "When Is Bad News Really Bad News?" *Journal of Finance*, vol. 57, 2507-2532.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 1998. "Investor Psychology and Security Market Over- and Under-reactions." *Journal of Finance*, vol. 53, 1839-1886.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam. 2001. "Overconfidence, Arbitrage, and Equilibrium Asset Pricing." *Journal of Finance*, vol. 56, 921-965.

De Long, J.B., A. Shleifer, L.G. Summers, and R.J. Waldmann. 1990. "Noise Trader Risk in Financial Markets." *Journal of Political Economy*. vol. 98, no. 4: 703-738.

Diamond, D. W. and R. E. Verrecchia. 1987. "Constraints on Short-Selling and Asset Price Adjustment to Private Information." *Journal of Financial Economics* 18, 277-311.

Diether, K. B., C. J. Malloy, and A. Scherbina. 2002. "Difference of Opinion and the Cross Section of Stock Returns." *Journal of Finance*, Vol. 57, No. 5, 2113-2141.

Doukas, J., C. Kim, and C. Pantzalis. 2004. "Divergent Opinions and the Performance of Value Stocks." *Financial Analyst Journal*, vol. 60, no. 6: 50-59.

Doukas, J., C. Kim, and C. Pantzalis. 2004. "Divergence of Opinions and Equity Returns under Different States of Earnings Expectations." Working paper.

Doukas, J., C. Kim, and C. Pantzalis. 2002. "A Test of the Errors-in-Expectations Explanation of the Value/Glamour Stock Returns Performance: Evidence from Analysts' Forecasts." *Journal of Finance* vol. 57, no. 5: 2143-2165.

Easley D. , N. M. Kiefer, and M. O'Hara. 1996. "Cream-Skimming or Profit-Sharing? The Curious Role of Purchased Order Flow." *Journal of Finance* vol. 51, 2143-2165.

Easley D. , N. M. Kiefer, and M. O'Hara. 2005. "Factoring Information into Returns." Working Paper, Cornell University.

Frazzini, A. 2006. "The Disposition Effect and Underreaction to News." *Journal of Finance* forthcoming.

Garman, M. B. and J. A. Ohlson. 1981. "Valuation of Risky Assets in Arbitrage Free Economies with Transaction Costs." *Journal of Financial Economics*, Vol. 9, 271-280.

Hong, H. and J. C. Stein. 2000. "Differences of Opinion, Rational Arbitrage and Market Crashes." Working paper, Stanford University.

Hong, H. and J. C. Stein. 1999. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, Vol. 54, No. 6, 2143-2184.

Hou, K. and T. J. Moskowitz. 2005. "Market Frictions, Price Delays, and the Cross-Section of Expected Returns." *The Reviews of Financial Studies*, Vol. 18, No. 3, 981-1020.

Jegadeesh, N. and S. Titman. 1995. "Overreaction, Delayed Reaction, and Contrarian Profits." *The Reviews of Financial Studies*, Vol. 8, No. 4, 973-993.

Jiang, G., C. M. C. Lee, and G. Y. Zhang. 2004. "Information Uncertainty and Expected Returns". *Review of Accounting Studies*, Vol. 10, No. 2-3, 185-221.

Johnson, T. 2004. "Forecast Dispersion and the Cross-section of Returns." *Journal of Finance*, Vol. 59, No. 5, 1957-1978.

King, B. 1966. "Market and Industry Factors in Stock Price Behavior." *Journal of Business*, vol. 39, 139-190.

Knez, O. and M. Ready. 1996. "Estimating the Profits from Trading Strategies." *Reviews of Financial Studies*, vol. 9, 1121-1163.

La Porta, R., J. Lakonishock, A. Shleifer and R. Vishny. 1997. "Good News for Value Stocks: Further Evidence on Market Efficiency." *Journal of Finance*, vol. 52, 859-874.

Lee, C.M.C., A. Shleifer, and R.D. Thaler. 1991. "Investor Sentiment and the Closed-End Fund Puzzle." Journal of Finance, vol. 46, no. 1:75-109.

Levy, H. 1978. "Equilibrium in an Imperfect Market: A Constraint on the Number of Securities in the Portfolio." *American Economic Review*, 643-658.

Lo, A. W., and A. C. MacKinlay. 1990. "When Are Contrarian Profits Due to Stock Market Overreaction?" *Review of Financial Studies*, vol. 3, 175-206.

Malkiel, B. G., and Y. Xu. 2004. "Idiosyncratic Risk and Security Returns." Working paper, Princeton University.

Mashruwala, C., S. Rajgopal, and T. Shevlin. 2005. "Why Is the Accrual Anomaly Not Arbitraged Away? The Role of Idiosyncratic Risk and Transaction Costs." *Forthcoming Journal of Accounting and Economics.*

Merton, R.C. 1987. "A Simple Model of Capital Market Equilibrium with Incomplete Information." *Journal of Finance*, vol. 42, 483-510.

Mendenhall, R. 2004. "Arbitrage Risk and Post-Earnings Announcement Drift. " *Journal of Business*, vol. 77, 875-894.

Neal, R., and S.M. Wheatley. 1998. "Do Measures of Investor Sentiment Predict Returns?" Journal of Financial and Quantitative Analysis, vol. 33, no. 4: 523-547.

Pastor, L. and Veronesi, P. 2004. "Was there a Nasdaq Bubble in the late 1990s?" CRSP working paper No. 557, University of Chicago.

Piotroski, J. D., and D. T. Roulstone. 2004. "The Influence of Analysts, Institutional Investors, and Insiders on the Incorporation of Market, Industry, and Firm-Specific Information into Stock Prices." *The Accounting Review*, vol. 79, no. 4: 1119-1151.

Pontiff, J., and M. J. Schill. 2004. " Long-Run Seasoned Equity Offering Returns: Data Snooping, Model Misspecification, Or Mispricing? A Costly Arbitrage Approach." Working paper, Boston College.

Pontiff, J. 1996. "Costly Arbitrage: Evidence from Closed-End Funds." *The Quarterly Journal of Economics,* Vol. 111, No. 4, 1135-1151.

Pontiff, J. 2005. "Costly Arbitrage and the Myth of Idiosyncratic Risk II." SSRN working paper.

Roll, R. 1988. " R^2 ." *Journal of Finance,* vol.43, 541-566.

Ross, S. A. 1989. "Information and Volatility: The No-Arbitrage Martingale Approach to Timing and Resolution Irrelevancy." *Journal of Finance*, vol. 44, 1-17.

Shleifer, A and R. Vishny. 1997. "The Limits of Arbitrage." *Journal of Finance*, vol. 52, no. 1, 35-55.

Skinner, D.J. and R.G. Sloan. 1998. "Earnings Surprises, Growth Expectations and Stock Returns or Don't Let an Earnings Torpedo Sink Your Portfolio." working paper, University of Michigan Business School.

Stoll, H. R. 2000. "Friction." *Journal of Finance*, vol. 55, no. 4, 1479-1514.

Wurgler, J., and E. Zhuravskaya. 2002. "Does Arbitrage Flatten Demand Curves for Stocks?" *Journal of Business*, vol. 75, 583-607.

Zhang, X.F. 2006. "Information Uncertainty and Stock Returns." *Journal of Finance*, vol. 61, no. 1, 105-136.

Table 1
Summary statistics of size-B/M ratio portfolio weekly returns: July, 1963 - May, 2005

Table 1reports the summary statistics of size-B/M ratio portfolio weekly returns over the July, 1963 to May, 2005 period. The sample includes 2188 weekly observations for each portfolio. The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. Portfolios are constructed in a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated into three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by the market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. LOW, MED, and HIGH refer to the low 30%, medium 40% and high 30% B/M portfolio in each size group.

				Autocorrelations (AC)									
	B/M		Standard	lag1		lag2		lag3		lag4		lag5	
size	Portfolio	Mean	deviation	AC1	Q-Stat	AC2	Q-Stat	AC3	Q-Stat	AC4	Q-Stat	AC5	Q-Stat
	LOW	0.1897	2.7284	0.197	85.308	0.087	101.970	0.087	118.500	0.033	120.950	0.019	121.730
Small	MED	0.2920	2.0224	0.231	117.600	0.101	140.040	0.082	154.810	0.049	160.130	0.028	161.860
	HIGH	0.3307	1.9883	0.242	129.300	0.133	168.100	0.097	188.630	0.045	193.060	0.028	194.830
	LOW	0.2060	2.2907	-0.010	0.207	0.012	0.511	0.038	3.756	-0.043	7.862	-0.010	8.083
Big	MED	0.2258	1.9426	0.014	0.456	0.024	1.776	0.021	2.739	-0.027	4.391	-0.041	8.169
	HIGH	0.2654	1.9648	0.052	5.931	0.056	12.897	0.018	13.631	-0.024	14.906	-0.044	19.096
	LOW	0.2010	2.2869	0.008	0.133	0.015	0.625	0.044	4.819	-0.039	8.104	-0.008	8.252
All	MED	0.2261	1.9283	0.032	2.270	0.028	4.026	0.021	5.017	-0.022	6.088	-0.029	7.902
	HIGH	0.2889	1.9293	0.088	16.849	0.069	27.355	0.031	29.405	-0.013	29.767	-0.026	31.235

Table 2
Cross-autocorrelation in weekly returns of size-B/M ratio portfolios: July, 1963 - May, 2005

The table presents the cross-autocorrelation of weekly returns of size-B/M portfolios. The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. Portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by the market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. R(g, t) and R(v, t) refer to the weekly returns of the low 30% B/M (glamour) portfolio and the high 30% B/M (value) portfolio at week t. R(g, t-i) and R(v, t-i) refer to the weekly return of the low 30% B/M (glamour) portfolio and the high 30% B/M (value) portfolio at week (t-i) (i=1,2,3,4). * for 5% level. ** for 1% level.

Cross-autocorrelation in weekly returns by B/M ratio

	Small			Big			All	
	R(g, t)	R(v, t)		R(g, t)	R(v, t)		R(g, t)	R(v, t)
R(g, t)	1.0000	0.9032 **	R(g, t)	1.0000	0.8020 **	R(g, t)	1.0000	0.8133 **
R(v, t)	0.9032 **	1.0000	R(v, t)	0.8020 *	1.0000	R(v, t)	0.8133 **	1.0000
R(g, t-1)	0.1970 **	0.2179 **	R(g, t-1)	-0.0097	0.0282	R(g, t-1)	0.00779	0.0608 **
R(v, t-1)	0.1687 **	0.2425 **	R(v, t-1)	-0.0273	0.0519 *	R(v, t-1)	-0.0132	0.0877 **
R(g, t-2)	0.0870 **	0.1168 **	R(g, t-2)	0.0118	0.0372	R(g, t-2)	0.0150	0.0461 *
R(v, t-2)	0.0702 **	0.1329 **	R(v, t-2)	-0.0024	0.0563 **	R(v, t-2)	0.0052	0.0692 **

Table 3
The cross-correlation between the lowest and highest B/M portfolio weekly returns: July, 1963 - May, 2005

Table 3 reports the cross-correlations between the lowest and highest B/M portfolio weekly returns estimated from the regression below:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \beta_{-2} R_{g,t-2} + \beta_{-3} R_{g,t-3} + \varepsilon_t \qquad [1]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \beta_{-2} R_{v,t-2} + \beta_{-3} R_{v,t-3} + \varepsilon_t \qquad [2]$$

R(g, t) and R(v,t) are the contemporaneous returns of the lowest (glamour) and highest (value) B/M portfolios. R(g, t-i) and R(v, t-i) are the excess returns i weeks earlier on the glamour and value portfolios (i = 1, 2, 3). The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. The portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

	Small		Big		All	
	Eq. [1]	Eq. [2]	Eq. [1]	Eq. [2]	Eq. [1]	Eq. [2]
α	0.1985 **	-0.1886 **	0.1156 **	-0.0165	0.1384 **	-0.0420
β(0)	0.6511 **	1.2618 **	0.6883 **	0.9417 **	0.6854 **	0.9759 **
β(-1)	0.0260 **	-0.0606 **	0.0312 **	-0.0795 **	0.0458 **	-0.0975 **
β(-2)	0.0234 **	-0.0559 **	0.0240 *	-0.0530 **	0.0284 **	-0.0542 **
β(-3)	-0.0006	-0.0030	-0.0123	0.0273	-0.0065	0.0153
R^2	0.8184	0.8200	0.6454	0.6504	0.6655	0.6706

Table 4

Weekly estimates of GARCH(1,1)-M models for lowest and highest B/M portfolios: July, 1963 - May, 2005

Table 4 reports the weekly estimates of GARCH(1,1)-M model for glamour and value portfolios:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t}$$
$$h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1} \qquad [3]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t}$$
$$h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1} \qquad [4]$$

R(v, t) and R(g,t) are the contemporaneous returns of the value and glamour portfolios. R(v, t-1) and R(g, t-1) are the excess returns 1 week earlier on the value and glamour portfolios. σ is the standard deviation of the conditional variance of the error term. The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. The portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

	Small		Big		All	
	Eq. [3]	Eq. [4]	Eq. [3]	Eq. [4]	Eq. [3]	Eq. [4]
α	0.0311	0.0048	-0.1923	0.0730	-0.1240	0.0823
β(0)	0.6716 **	1.2104 **	0.7211 **	0.8814 **	0.7115 **	0.8997 **
β(-1)	0.0356 **	-0.0626 **	0.0274 **	-0.0616 **	0.0478 **	-0.0777 **
γ	0.1964 *	-0.1585	0.2860 **	-0.0584	0.2445 *	-0.0870
a	0.0303 **	0.0498 **	0.0222 **	0.0389 **	0.0606 **	0.0409 **
b	0.1043 **	0.1171 **	0.0551 **	0.1046 **	0.0907 **	0.1071 **
c	0.8549 **	0.8457 **	0.9283 **	0.8753 **	0.8651 **	0.8741 **
log likelihood	-2592.7868	-3208.25	-3323.75	-3551.03	-3255.41	-3511.38
R^2	0.82	0.82	0.64	0.65	0.66	0.67

Table 5

The volatility spillover between the lowest and highest B/M portfolio weekly returns: July, 1963 - May, 2005

Table 5 reports the volatility spillover between the lowest and highest B/M portfolio weekly returns using GARCH-M model:

$$R_{v,t} = \alpha + \beta_0 R_{g,t} + \beta_{-1} R_{g,t-1} + \gamma\sigma_{v,t} + \varepsilon_{v,t}$$
$$h_{v,t} = a + b\varepsilon^2_{v,t-1} + ch_{v,t-1} + d\varepsilon^2_{g,t-1} \qquad [5]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{v,t} + \beta_{-1} R_{v,t-1} + \gamma\sigma_{g,t} + \varepsilon_{g,t}$$
$$h_{g,t} = a + b\varepsilon^2_{g,t-1} + ch_{g,t-1} + d\varepsilon^2_{v,t-1} \qquad [6]$$

R(v, t) and R(g,t) are the contemporaneous returns of the value and glamour portfolios. R(v, t-1) and R(g, t-1) are the excess return 1 week earlier on the value and glamour portfolios. σ is the standard deviation of the conditional variance of the error term. d measures the impact of past volatility surprises of the glamour portfolio on the conditional variance of value portfolio in Eq.[5], and in Eq.[6], d measures the impact of past volatility surprises of the value portfolio on the conditional variance of glamour portfolio. The volatility surprises, ε^2(g, t-1) and ε^2(v, t-1) are lagged squared residuals derived from Eq. [4] and [3] respectively. The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. Portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by the market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

	Small				Big				All			
	Eq. [5]		Eq. [6]		Eq. [5]		Eq. [6]		Eq. [5]		Eq. [6]	
α	0.0110		0.0048		-0.1482		0.0730		-0.1148		0.0823	
β(0)	0.6716	**	1.2104	**	0.7207	**	0.8814	**	0.7108	**	0.8997	**
β(-1)	0.0357	**	-0.0626	**	0.0269	**	-0.0616	**	0.0473	**	-0.0777	**
γ	0.2228	*	-0.1585		0.2412	*	-0.0584		0.2337	*	-0.0870	
a	0.0313	**	0.0498	**	0.0280	**	0.0389	**	0.0615	**	0.0409	**
b	0.0847	**	0.1171	**	0.0482	**	0.1046	**	0.0665	**	0.1071	**
c	0.8472	**	0.8457	**	0.9122	**	0.8753	**	0.8583	**	0.8741	**
d	**0.0141**	**	**1.0000E-06**		**0.0141**	**	**8.8090E-20**		**0.0216**	**	**6.3790E-21**	
log likelihood	-2589.89		-3208.25		-3318.17		-3551.03		-3248.85		-3511.38	
R^2	0.82		0.82		0.64		0.65		0.66		0.67	

Table 6

Regressions of zero net investment on value-weighted market returns: July, 1963 - May, 2005

This table reports the results from regressing the difference between the weekly returns on glamour and value portfolios within each size group, on value-weighted market returns:

$$R_{g,t} - R_{v,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \varepsilon_t$$

$$h_t = a + b\,\varepsilon_{t-1}^2 + ch_{t-1} \qquad [1]$$

R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest (glamour) and highest B/M (value) portfolios. β(0) is the current beta and ∑ β(-1, -k) refers to the sum of lagged betas. The regressions are fitted with 3 and 5 lags (k=3 and k=5). The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. Portfolios are constructed by a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

	A. 3 lags			B. 5 lags		
	Small	Big	All	Small	Big	All
α	-0.1451 **	-0.0601 *	-0.0792 **	-0.1447 **	-0.0614 *	-0.0769 **
β(0)	**0.3025** **	**0.1925** **	**0.2157** **	**0.3026** **	**0.1927** **	**0.2147** **
β(-1)	0.0173	-0.0571 **	-0.0763 **	0.0171	-0.0562 **	-0.0754 **
β(-2)	-0.0261 **	-0.0282 *	-0.0403 **	-0.0263 **	-0.0282 *	-0.0396 **
β(-3)	0.0059	0.0103	-0.0046	0.0058	0.0097	-0.0043
β(-4)				0.0076	-0.0093	-0.0197
β(-5)				-0.0059	0.0189	0.0029
$\sum_{k=1}^{k}\beta_{-k}$	**-0.0029** **	**-0.0750** **	**-0.1212** **	**-0.0017** *	**-0.0651** **	**-0.1361** **
a	0.0532 **	0.0335 **	0.0603 **	0.0542 **	0.0328 **	0.0586 **
b	0.1411 **	0.0681 **	0.0905 **	0.1432 **	0.0678 **	0.0889 **
c	0.8112 **	0.9109 **	0.8722 **	0.8081 **	0.9117 **	0.8749 **
log likelihood	-2978.96	-3494.77	-3419.40	-2976.09	-3491.18	-3416.06
R^2	0.33	0.14	0.17	0.33	0.14	0.17

Table 7

Regressions of B/M portfolio weekly returns on value-weighted market returns: July, 1963 - May, 2005

This table reports the results from regressing the weekly returns of glamour and value portfolios within each size group, on value-weighted market returns:

$$R_{v,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \gamma\sigma_t + \varepsilon_t$$
$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \qquad [2]$$

and

$$R_{g,t} = \alpha + \beta_0 R_{m,t} + \sum_{k=1}^{k} \beta_{-k} R_{m,t-k} + \gamma\sigma_t + \varepsilon_t$$
$$h_t = a + b\varepsilon_{t-1}^2 + ch_{t-1} \qquad [3]$$

R(g, t) and R(v, t) are the contemporaneous excess returns of the lowest (glamour) and highest B/M (value) portfolios. σ is the standard deviation of the conditional variance of the error term. β(0) is the current beta and ∑ β(-1, -k) refers to the sum of lagged betas. The regressions are fitted with 5 lags (k=5). The weekly returns are calculated as average daily returns during the week, and all the daily portfolio return data from July 1, 1963 to May 31, 2005 are from Professor Kenneth French's website. Portfolios are constructed in a two-by-three sort on size and B/M. Within each of the two size quartiles, the stocks are further allocated to three book-to-market portfolios. The size breakpoint for year t is the median NYSE market equity at the end of June of year t. B/M for June of year t is the book equity for the last fiscal year ending in t-1 divided by market equity for December of t-1. The B/M breakpoints are the 30th and 70th NYSE percentiles. * for 5% level. ** for 1% level.

	Small		Big		All	
	Eq. [2]	Eq. [3]	Eq. [2]	Eq. [3]	Eq. [2]	Eq. [3]
α	-0.1796 *	0.0399	0.0279	-0.0270	0.0446	-0.0386
β(0)	**0.7860** **	**1.1382** **	**0.8861** **	**1.0769** **	**0.8704** **	**1.0797** **
β(-1)	0.1800 **	0.2109 **	-0.0010	-0.0541 **	0.0436 **	-0.0376 **
β(-2)	0.0477 **	0.0311 **	0.0109	-0.0134 **	0.0242 **	-0.0103 *
β(-3)	0.0333 **	0.0352 **	-0.0249 **	-0.0092	-0.0008	-0.0041
β(-4)	0.0394 **	0.0425 **	-0.0006	-0.0119 *	0.0168 *	-0.0068
β(-5)	0.0324 **	0.0199	-0.0167 *	-0.0012	0.0079	0.0014
$\sum_{k=1}^{k} \beta_{-k}$	0.3328 **	0.3396 **	-0.0323 *	-0.0898 **	0.0917 **	-0.0573 **
γ	**0.3889** **	**-0.0046**	**0.1854** **	**0.2362**	**0.1779** *	**0.2651**
a	0.052 **	0.0443 **	0.0144 **	0.0531 **	0.0295 **	0.0599 **
b	0.1171 **	0.0698 **	0.0736 **	0.1206 **	0.1143 **	0.1453 **
c	0.8382 **	0.9021 **	0.9091 **	0.7042 **	0.8601 **	0.6231 **
log likelihood	-3022.09	-3465.5	-2725.6	-1712.5	-2699.7	-1521.8
R^2	73.36%	78.61%	75.58%	94.43%	77.58%	95.28%

Table 8
Summary statistics of arbitrage cost variables: 1987 - 2005

Table 8 reports summary statistics of arbitrage cost variables for both exchange-traded and NASDAQ stocks. All values are calendar year based data. Panel A reports full sample summary statistics. Panels B and C report summary statistics for value and glamour stocks respectively. Value, medium and glamour portfolios are three equal sized book-to-market portfolios formed at the beginning of each calendar year from 1987 to 2005. Value portfolio is consist of highest 33% B/M ratio stocks, medium portfolio is consist of medium 33% B/M ratio stocks, and glamour portfolio is consist of lowest 33% B/M ratio stocks. B/M is the ratio of book value of common equity to market value of the equity at the end of prior calendar year. IDIO_MKT is the residual standard error from a market model regression of the stocks' daily excess returns on those of the CRSP value-weighted index over a year. IDIO_FF is the residual standard error from a FF-three factor model regression of the stocks' daily returns over a year. PRICE is the closing daily stock price averaged over all trading days during a year. VOLUME is the closing daily stock price times daily shares traded averaged over all trading days during a year (in millions of dollars).

	Panel A. Full Sample				
	B/M	IDIO_MKT	IDIO_FF	PRICE	VOLUME
Mean	0.870	0.0412	0.0408	17.444	9.412
Std. Dev	24.715	0.0324	0.0323	21.724	58.333
N	66568	66552	66534	66568	66568
	Panel B. Value Stocks				
Mean	1.861	0.047	0.047	11.093	2.128
Std. Dev	42.792	0.039	0.039	17.460	12.689
N	22188.000	22184	22178	22188	22188
	Panel C. Glamour Stocks				
Mean	0.220	0.041	0.040	22.545	19.899
Std. Dev	0.108	0.030	0.030	27.233	96.561
N	22184.000	22177	22170	22184	22184

Table 9

Comparison of arbitrage cost of different B/M portfolios: 1987-2005

Table 9 reports arbitrage costs statistics of three book-to-market portfolios. The value, medium and glamour portfolios are three equal sized book-to-market portfolios formed at the beginning of each calendar year from 1987 to 2005. The value portfolio consists of highest 33% B/M ratio stocks, the medium portfolio consists of medium 33% B/M ratio stocks, and the glamour portfolio consists of lowest 33% B/M ratio stocks. All values are calendar year based data. B/M is the ratio of book value of common equity to market value of the equity at the prior calendar year end. PRICE is the closing daily stock price averaged over all trading days during a year. VOLUME is the closing daily stock price times daily shares traded averaged over all trading days during a year (in millions of dollars). IDIO_MKT is the residual standard error from a market model regression of the stocks' daily excess returns on those of the CRSP value-weighted index over a year. IDIO_FF is the residual standard error from a FF-three factor model regression of the stocks' daily returns over a year. * for 5% level , ** for 1% level.

A. IDIO_MKT

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	All Years
value	0.038	0.038	0.038	0.050	0.054	0.055	0.050	0.045	0.044	0.043	0.042	0.053	0.055	0.057	0.064	0.053	0.046	0.031	0.028	0.047
medium	0.033	0.030	0.027	0.033	0.033	0.035	0.034	0.034	0.035	0.035	0.035	0.040	0.042	0.048	0.045	0.039	0.030	0.026	0.025	0.035
glamour	0.037	0.032	0.029	0.035	0.034	0.041	0.040	0.041	0.040	0.042	0.042	0.047	0.048	0.062	0.050	0.044	0.032	0.032	0.030	0.041
diff. (V-G)	0.001	0.006	0.009	0.015	0.020	0.015	0.010	0.004	0.004	0.001	0.000	0.006	0.007	-0.005	0.014	0.009	0.014	-0.001	-0.002	0.006
		**	**	**	**	**	**	**	**			**	**	*	**	**	**		**	**

B. IDIO_FF

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	All Years
value	0.037	0.038	0.038	0.050	0.054	0.055	0.050	0.045	0.044	0.043	0.042	0.052	0.055	0.056	0.063	0.053	0.046	0.031	0.028	0.047
medium	0.032	0.030	0.027	0.032	0.033	0.035	0.034	0.034	0.035	0.035	0.035	0.039	0.042	0.048	0.044	0.039	0.030	0.025	0.025	0.035
glamour	0.035	0.032	0.029	0.035	0.034	0.040	0.040	0.040	0.040	0.041	0.042	0.046	0.047	0.060	0.049	0.043	0.032	0.032	0.029	0.040
diff. (V-G)	0.001	0.006	0.009	0.015	0.020	0.015	0.010	0.005	0.004	0.002	0.000	0.006	0.007	-0.004	0.014	0.010	0.014	-0.001	-0.002	0.007
		**	**	**	**	**	**	**	**			**	**	*	**	**	**		**	**

C. PRICE

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	All Years
value	14.942	12.114	12.098	9.565	9.257	8.935	11.088	11.493	11.722	12.186	13.185	11.684	8.808	9.375	6.865	7.780	7.974	15.213	18.072	11.093
medium	21.201	16.009	18.894	17.640	17.794	18.936	19.581	18.523	18.463	19.531	20.838	18.734	17.276	18.310	16.579	16.578	16.652	21.800	21.999	18.694
glamour	22.737	19.168	21.573	21.463	24.898	20.125	19.571	18.214	20.456	22.184	21.908	22.943	26.338	31.759	22.352	19.957	22.390	22.300	23.355	22.545
diff. (V-G)	-7.79	-7.05	-9.48	-11.90	-15.64	-11.19	-8.48	-6.72	-8.73	-10.00	-8.72	-11.26	-17.53	-22.38	-15.49	-12.18	-14.42	-7.09	-5.28	-11.45
	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**

D. VOLUME

	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	All Years
value	1.600	0.929	0.877	0.628	0.675	0.563	0.924	0.760	0.975	1.011	1.409	1.537	1.059	1.357	1.603	1.857	2.981	6.813	10.408	2.128
medium	2.828	1.433	2.077	1.815	1.796	2.443	2.669	2.894	3.666	4.124	5.129	4.880	4.939	7.760	7.390	8.355	9.177	15.735	19.160	6.234
glamour	3.463	2.556	3.154	3.639	4.891	4.055	5.224	5.191	7.684	9.966	12.920	16.772	30.925	55.173	37.802	30.915	29.309	30.430	34.312	19.899
diff. (V-G)	-1.86	-1.63	-2.28	-3.01	-4.22	-3.49	-4.30	-4.43	-6.71	-8.95	-11.51	-15.23	-29.87	-53.82	-36.20	-29.06	-26.33	-23.62	-23.90	-17.77
	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**	**

Table 10
Portfolio Post-Earnings Announcement Returns by B/M Ratio: 1st Quarter of 1994 - 3rd Quarter of 2005

Table 10 reports the average monthly portfolio returns at month (t+1), (t+2), and (t+3) following earnings announcement sorted by the nature of news and B/M ratio. Starting from the first quarter of 1994, at each quarterly earnings announcement we classify earnings surprises into three equal sized news groups based on the cumulative abnormal return in the 3-day window (-1, 0, 1), and we define the group with the lowest 33% CAR as the Bad news group and the group with the highest 33% CAR as the Good news group. Within both the Good and Bad earnings surprise, stocks are further sorted into five equal sized B/M quintiles based on the B/M ratio calculated at the end of the fiscal year preceding the quarterly earnings announcement. Portfolio returns are equally weighted. The t-statistics are in parentheses and above 10% statistical significance is indicated in bold.

	Post Earnings Announcement Portfolio Monthly Returns					
	Month t+1		Month t+2		Month t+3	
Sorted by	Earnings news		Earnings news		Earnings news	
B/M ratio	Bad	Good	Bad	Good	Bad	Good
Q1 (glamour)	0.0027	0.0096	0.0067	0.0107	0.0052	0.0113
Q5 (value)	0.0062	0.0246	0.0181	0.0260	0.0176	0.0291
Q5-Q1	0.0035	**0.0150**	**0.0114**	**0.0153**	**0.0124**	**0.0178**
	(0.87)	(4.70)	(3.57)	(5.31)	(3.77)	(5.48)

Table 11
Post-Earnings Announcement Monthly Alphas by B/M Ratio: 1st Quarter of 1994 - 3rd Quarter of 2005

Table 11 reports the monthly alphas of value and glamour portfolios for each of the three months following the earnings news. Starting from the first quarter of 1994, for each quarterly earnings announcement we classify earnings surprises into three equal sized news groups based on the cumulative abnormal return in the 3-day window (-1, 0, 1), and we define the group with the lowest 33% CAR as the Bad news group and the group with the highest 33% CAR as the Good news group. Within both the Good and Bad earnings groups, stocks are further sorted into five equal sized B/M quintiles based on the B/M ratio calculated at the end of the fiscal year preceding the quarterly earnings announcement. D1 and D5 refer to the lowest (glamour) and the highest B/M (value) portfolios respectively. Portfolio returns are equally weighted. Monthly alphas are computed relative to the following Fama-French three factor model:

$$R_{it} = \alpha + \beta R_{mt} + \delta SMB_t + \phi HML_t + \varepsilon_{it}$$

where R(it) is the monthly return of the highest (value) and the lowest B/M (glamour) portfolios in excess of one-month treasury bill rate. R(mt) is the value-weighted market return in excess of one-month treasury bill rate. The SMB and HML are size premium and value premium factors. Alphas represent the abnormal returns. The t-statistics are in parentheses and above 5% statistical significance is indicated in bold.

	Post Earnings Announcement Portfolio Monthly Alphas					
	Month t+1		Month t+2		Month t+3	
Sorted by	Earnings news		Earnings news		Earnings news	
B/M ratio	Bad	Good	Bad	Good	Bad	Good
Q1 (glamour)	-0.2789	0.1197	0.0231	**0.5025**	0.1329	0.3909
	(-1.16)	(0.48)	(0.10)	(2.40)	(0.58)	(1.66)
Q5 (value)	**-0.7945**	**0.8527**	**1.4567**	**1.7069**	**1.6064**	**2.8412**
	(-3.91)	(3.91)	(6.93)	(8.87)	(6.63)	(13.18)

Table 12

Determinants of Asymmetric Post-Earnings Announcement Drift between Value and Glamour stocks : 1st Quarter of 1994 - 3rd Quarter of 2005

Table 12 reports the estimation results of the following regression. Panels A and B report the estimation results when the dependent variable QEA is the abnormal return compounded 3 months and 2 months following earnings announcements respectively.

$$QEA_{i,q} = a + bCAR_{i,q} + c(CAR_{i,q} * BM_{i,q}) + d(CAR_{i,q} * IDIO_{i,q}) + e(CAR_{i,q} * VOLUME_{i,q}) + \varepsilon_{i,q} \quad [3]$$

QEA is the compound abnormal return from the first month through the third month following the earnings announcement. The compound abnormal return is computed as the buy and hold return on each stock minus the buy and hold return on the CRSP value weighted index. CAR is the market model cumulative abnormal return for the 3-day window (-1, +1) around the earnings announcements. BM is B/M ratio calculated at the end of the fiscal year preceding the announcement. IDIO is the mean residual error from market model regression estimated over trading days -255 to -2 relative to the announcement. VOLUME is the closing daily stock price times daily shares traded averaged over trading days -255 to -2 relative to the announcement. ALL independent variables have been converted to coded scores ranging from -0.5 to 0.5 based on their ranking within pooled earnings announcement observations. All coefficients have been multiplied by 10. Above 10% statistical significance is indicated in bold.

	Panel A: 3 months compounding			
Variables	Coefficients	t-statistics	Coefficients	t-statistics
Intercept	**-0.563**	-23.24	**-0.556**	-22.92
CAR	**1.662**	21.88	**1.513**	18.82
CAR*BM	**0.543**	2.37	0.246	0.96
CAR*IDIO			**1.348**	4.86
CAR*VOLUME			**-0.573**	-2.01
Adj-R^2	28.00%		0.30%	

	Panel B: 2 months compounding			
Variables	Coefficients	t-statistics	Coefficients	t-statistics
Intercept	**-0.304**	-10.33	**-0.298**	-10.12
CAR	**1.68**	18.23	**1.564**	16.07
CAR*BM	**0.483**	1.74	0.209	0.67
CAR*IDIO			**1.034**	3.08
CAR*VOLUME			-0.553	-1.60
Adj-R^2	0.19%		0.20%	

Table 13
Determinants of Asymmetric Post-Earnings Announcement Drift between Value and Glamour stocks: Extreme Earnings News Analysis

Table 13 reports the estimation results of the following regression for the extreme news observations. Panels A and B report the estimation results when the dependent variable QEA is the abnormal return compounded 3 months and 2 months following earnings announcements respectively.

$$QEA_{i,q} = a + b(BM_{i,q}) + c(IDIO_{i,q}) + d(VOLUME_{i,q}) + \varepsilon_{i,q} \qquad [4]$$

Earnings surprises in the highest (lowest) 10% CAR decile is defined as extreme good (bad) news. CAR is the market model cumulative abnormal return for the 3-day window (-1, +1) around the earnings announcements. QEA is the compound abnormal return from the first month through the third month following the earnings announcement. The compound abnormal return is computed as the buy and hold return on each stock minus the buy and hold return on the CRSP value weighted index. QEA is the dependent variable for extreme good news announcements and QEA times -1.0 is the dependent variable for extreme bad news announcements. BM is B/M ratio calculated at the end of the fiscal year preceding the announcement. IDIO is the mean residual error from market model regression estimated over trading days -255 to -2 relative to the announcement. VOLUME is the closing daily stock price times daily shares traded averaged over trading days -255 to -2 relative to the announcement. ALL independent variables have been converted to coded scores ranging from -0.5 to 0.5 based on their ranking within extreme earnings news observations. All coefficients have been multiplied by 10. Above 10% statistical significance is indicated in bold.

	Panel A: 3 months compounding		Panel B: 2 months compounding	
Variables	Coefficients	t-statistics	Coefficients	t-statistics
Intercept	**1.085**	15.86	**1.098**	13.11
BM	0.002	0.09	0.206	0.69
IDIO	**0.688**	2.96	**0.521**	1.83
VOLUME	-0.393	-1.51	-0.309	-0.97
Adj-R^2	0.04%		0.02%	

Table 14

Asymmetric Drift - Idiosyncratic Risk Relationship between Value and Glamour stocks: 1st Quarter of 1994 – 3rd Quarter of 2005

Table 14 reports the estimation results of the following regression. Panels A and B report the estimation results for stocks in the value and glamour portfolios separately.

$$QEA_{i,q} = a + bCAR_{i,q} + c(CAR_{i,q} * IDIO_{i,q}) + d(CAR_{i,q} * VOLUME_{i,q}) + \varepsilon_{i,q} \qquad [5]$$

B/M portfolios are sorted based on the B/M ratio calculated at the end of the fiscal year preceding earnings announcement for the pooled earnings announcement observations. We define the lowest 20% B/M quintile as glamour portfolio and the highest 20% B/M quintile as value portfolio. QEA is the compound abnormal return from the first month through the third month following the earnings announcement. The compound abnormal return is computed as the buy and hold return on each stock minus the buy and hold return on the CRSP value weighted index. CAR is the market model cumulative abnormal return for the 3-day window (-1, +1) around the earnings announcements. IDIO is the mean residual error from market model regression estimated over trading days -255 to -2 relative to the announcement. VOLUME is the closing daily stock price times daily shares traded averaged over trading days -255 to -2 relative to the announcement. All three independent variables have been converted to coded scores ranging from -0.5 to 0.5 based on their ranking within the value and glamour portfolios separately. All coefficients have been multiplied by 10. Above 10% statistical significance is indicated in bold.

	Panel A: value stocks		Panel B: glamour stocks	
Variables	Coefficients	t-statistics	Coefficients	t-statistics
Intercept	**0.410**	7.05	**-1.519**	-24.59
CAR	**2.178**	11.40	**1.622**	8.08
CAR*IDIO	**1.310**	2.04	0.646	0.95
CAR*VOLUME	0.173	0.29	-0.400	-0.62
Adj-R^2	0.46%		0.22%	

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